## 6 Online Appendix (Not for Publication)

### 6.1 Existence of Optimal Deterministic Mechanism

In this appendix, we establish that an optimal deterministic mechanism exists.

Proposition 3 There exists an optimal deterministic mechanism.

Proof. It suffices to show that for any $\left\{r_{1}, \ldots, r_{L}\right\} \subset\{1, \ldots, T\}$ there exists an optimal mechanism in which the principal offers the stopping plan where the number of failures born by agents is described by the set $\left\{r_{1}, \ldots, r_{L}\right\}$. Notice that an incentive-compatible mechanism $\mathcal{M}$ leads to $L$ mappings $\theta \rightarrow$ $\left(a_{i}(\theta), b_{i}(\theta)\right)$ for $i \in\{1, \ldots, L\}$, where $a_{l}(\theta)$ stands for for the firm's lump-sum payment and $b_{l}(\theta)$ for the success bonus of a type $\tau=(\theta, c)$ who chooses a stopping plan with tolerance for $r_{l}$ failures. Let $\pi^{*}$ be the supremum of all payoffs obtained by mechanisms in which the principal offers the action plans $\left\{r_{1}, \ldots, r_{L}\right\}$. We will show that there exists a mechanism $\mathcal{M}^{*}$ that yields the payoff $\pi^{*}$ to the principal. For each $n \in \mathbb{N}$, take a sequence of mechanisms $\mathcal{M}_{n}$ yielding a payoff to the principal at least as large as $\pi^{*}-n^{-1}$. The mechanism $\mathcal{M}_{n}$ leads to the mappings $\left(a_{i}^{n}(\theta), b_{i}^{n}(\theta)\right)$ for $i \in\{1, \ldots, L\}$ and to the threshold curves $v_{r_{l}}^{n}(\theta)$. Define $\theta_{r_{l}}^{n} \equiv \inf \left\{\theta^{\prime}: v_{r_{l}}^{n}\left(\theta^{\prime}\right)>0\right\}$ for $l \in\{1, \ldots, L\}$. We will use the mappings $\left(a_{i}^{n}(\theta), b_{i}^{n}(\theta)\right)(i \in\{1, \ldots, L\}, n \in \mathbb{N})$ to construct our mechanism $\mathcal{M}^{*}$.

It is easy to show that we can restrict attention to mechanisms for which $b_{i}^{n}(\theta) \geq 0$ for all $\theta$. Next, we claim that for each $m \in \mathbb{N}$ and $i \in\{1, \ldots, L\}$ we have

$$
\begin{equation*}
\sup _{n} \max _{\theta \in\left[0,1-m^{-1}\right]} b_{i}^{n}(\theta)<\infty \tag{29}
\end{equation*}
$$

Assume towards a contradiction that there is $m \in \mathbb{N}$ and a subsequence for which

$$
\sup _{n} \max _{\theta \in\left[0,1-m^{-1}\right]} b_{i}^{n}(\theta)=\infty
$$

Notice that the payoff of any type $\theta^{\prime} \in\left[1-\frac{1}{2 m}, 1\right]$ from choosing an allocation designed for a type $\theta^{\prime \prime} \in\left[0,1-\frac{1}{m}\right]$ is at least

$$
a_{i}^{n}\left(\theta^{\prime \prime}\right)+b_{i}^{n}\left(\theta^{\prime \prime}\right) \cdot D_{i}\left(\theta^{\prime}\right)-\left(\sum_{t=1}^{T} \delta^{t-1}\right) \cdot \bar{c},
$$

where $D_{i}\left(\theta^{\prime}\right) \equiv\left[\sum_{t=1}^{r_{i}} \delta^{t-1} \lambda+\left(1-(1-\lambda)^{r_{i}}\right) \cdot \sum_{t=r_{i}+1}^{T} \delta^{t-1} \lambda\right] \cdot \theta^{\prime}$. Since $a_{i}^{n}\left(\theta^{\prime \prime}\right)+b_{i}^{n}\left(\theta^{\prime \prime}\right) \cdot D_{i}\left(\theta^{\prime \prime}\right) \geq 0$ the expression above is at least as large as

$$
\begin{equation*}
b_{i}^{n}\left(\theta^{\prime \prime}\right) \cdot\left(D_{i}\left(\theta^{\prime}\right)-D_{i}\left(\theta^{\prime \prime}\right)\right)-\left(\sum_{t=1}^{T} \delta^{t-1} \lambda\right) \cdot \bar{c} \tag{30}
\end{equation*}
$$

Hence, we conclude that (30) diverges to $\infty$. Consequently, so does the payoff of all types $\theta^{\prime} \in$ $\left[1-\frac{1}{2 m}, 1\right]$, which automatically implies that the principal obtains a negative payoff whenever $n$ is large enough.

We will construct a contract $\left(a_{i}(\theta), b_{i}(\theta)\right)=\left\{\left(a_{i}(\theta), b_{i}(\theta)\right)\right\}_{i=1}^{L}$ from the sequence of contracts $\left\{\left(a_{i}^{n}(\theta), b_{i}^{n}(\theta)\right)\right\}_{i=1}^{L}$. Notice that $b_{i}^{n}:\left[\theta_{r_{i}}^{n}, 1\right) \rightarrow \mathbb{R}$ is increasing, while $a_{i}^{n}:\left[\theta_{r_{i}}^{n}, 1\right) \rightarrow \mathbb{R}$ is decreasing. Notice that we may extend $\left(a_{i}^{n}(\theta), b_{i}^{n}(\theta)\right)$ to $[0,1)$ by letting $\left(a_{i}^{n}(\theta), b_{i}^{n}(\theta)\right)=\left(a_{i}^{n}\left(\theta_{r_{i}}^{n}\right), b_{i}^{n}\left(\theta_{r_{i}}^{n}\right)\right)$ for all $\theta \leq \theta_{r_{i}}^{n \prime}$ (notice that zero-measure sets have no impact on payoffs). Notice that (29) imply that $b_{i}^{n}(\theta)$ is monotonic and uniformly bounded over the interval $\left[0,1-m^{-1}\right]$ (for each $m$ ) and, thus, Helly's First Theorem (Theorem 6.1.18 in Kannan and Krueger 1996) asserts that there exists a subsequence $b_{i}^{n_{m}}(\theta)$ which converges (a.e.) over $\left[0,1-m^{-1}\right]$. This property is also true for $\left[0,1-(m+z)^{-1}\right]$ for all $z \in \mathbb{N}$, and hence we can find a subsequence of $b_{i}^{n_{m}}(\theta)$, call it $b_{i}^{n_{m+1}}(\theta)$, which converges over $\left[0,1-(m+1)^{-1}\right]$. Proceeding inductively (by a diagonal argument) we obtain a subsequence of $b_{i}^{n}(\theta)$, call it $b_{i}^{n}(\theta)$, and an increasing function $b_{i}(\theta)$ such that $b_{i}^{n}(\theta) \rightarrow b_{i}(\theta)$ for almost all $\theta \in[0,1)$. Since $\left(a_{i}^{n}(\theta)\right)$ is decreasing the same argument implies that we may take a subsequence $\left(a_{i}^{n \prime}(\theta)\right)$ of $\left(a_{i}^{n}(\theta)\right)$ and a function $a_{i}(\theta)$ such that $a_{i}^{n}(\theta) \rightarrow a_{i}(\theta)$ for almost all $\theta \in[0,1)$.

Proceeding analogously for all $i \in\{1, \ldots L\}$, we obtain $\left\{\left(a_{1}(\theta), b_{1}(\theta)\right), \ldots,\left(a_{L}(\theta), b_{L}(\theta)\right)\right\}$. We must show that

$$
\begin{equation*}
\pi^{*}=\int_{0}^{1} \Pi(a(\theta), b(\theta)) f(\theta) d \theta \tag{31}
\end{equation*}
$$

Let $S \equiv T \Delta$ and notice that $\Pi(a(\theta), b(\theta))-S \leq 0$ for all $\theta$. Let $\mathbf{1}_{\left[\theta \leq 1-m^{-1}\right]}$ be the indicator function for $\theta \leq 1-m^{-1}$ and define $g^{m}$ by

$$
g^{m}(\theta) \equiv(\Pi(a(\theta), b(\theta))-S) \cdot f(\theta) \cdot \mathbf{1}_{\left[\theta \leq 1-m^{-1}\right]}(\theta) .
$$

Notice that $g_{m}$ is a decreasing sequence of nonpositive functions. Hence by the Lebesgue's monotone convergence theorem:

$$
\begin{equation*}
\int_{0}^{1}(\Pi(a(\theta), b(\theta))-S) f(\theta) d \theta=\lim _{m} \int_{0}^{1} g_{m}(\theta) d \theta \tag{32}
\end{equation*}
$$

We claim that $\int_{0}^{1}(\Pi(a(\theta), b(\theta))-S) f(\theta) d \theta>-\infty$. Assume towards a contradiction that

$$
\int_{0}^{1}(\Pi(a(\theta), b(\theta))-S) f(\theta) d \theta=-\infty .
$$

In this case we can find $\bar{m} \in \mathbb{N}$ such that $\int_{0}^{1} g_{\bar{m}}(\theta) d \theta<-4 S$ and hence

$$
\int_{0}^{1} \Pi(a(\theta), b(\theta)) \cdot f(\theta) \cdot \mathbf{1}_{\left[\theta \leq 1-\bar{m}^{-1}\right]}(\theta) d \theta<-3 S .
$$

Thus we can find $n^{*} \in \mathbb{N}$ such that $n>n^{*}$ implies

$$
\begin{equation*}
\int_{0}^{1} \Pi\left(a^{n}(\theta), b^{n}(\theta)\right) \cdot f(\theta) \cdot \mathbf{1}_{\left[\theta \leq 1-\bar{m}^{-1}\right]}(\theta) d \theta<-2 S \tag{33}
\end{equation*}
$$

Since $\int_{0}^{1} \Pi\left(a^{n}(\theta), b^{n}(\theta)\right) \cdot f(\theta) \cdot \mathbf{1}_{\left[\theta>1-\bar{m}^{-1}\right]}(\theta) d \theta<S$, (33) implies

$$
\begin{equation*}
\int_{0}^{1} \Pi\left(a^{n}(\theta), b^{n}(\theta)\right) \cdot f(\theta)(\theta) d \theta<-S \tag{34}
\end{equation*}
$$

which contradicts the assumption that $\int \Pi\left(a^{n}(\theta), b^{n}(\theta)\right) \cdot f(\theta)(\theta) d \theta>\pi^{*}-\frac{1}{n} \geq-\frac{1}{n}$ whenever $n>S^{-1}$. Thus we have $\int_{0}^{1} \Pi(a(\theta), b(\theta)) f(\theta) d \theta>-\infty$.

Take $\varepsilon>0$. We must show that

$$
\begin{equation*}
\int_{0}^{1} \Pi(a(\theta), b(\theta)) f(\theta) d \theta \geq \pi^{*}-\varepsilon \tag{35}
\end{equation*}
$$

to establish (31). Since $\int_{0}^{1} \Pi(a(\theta), b(\theta)) f(\theta) d \theta>-\infty$, (32) implies that there is $m_{1} \in \mathbb{N}$ such that $n>m_{1}$ implies

$$
\int_{1-m_{1}^{-1}}^{1} \Pi(a(\theta), b(\theta)) f(\theta) d \theta>-\frac{\varepsilon}{4} .
$$

Notice also that

$$
\int_{0}^{1} \Pi\left(a^{n}(\theta), b^{n}(\theta)\right) \cdot f(\theta) \cdot \mathbf{1}_{\left[\theta>1-m^{-1]}\right.}(\theta) d \theta<S \cdot\left(1-F\left(1-m^{-1}\right)\right) .
$$

Thus we take $m_{2} \geq m_{1}$ such that $S \cdot\left(1-F\left(1-m_{2}^{-1}\right)\right)<\frac{\varepsilon}{4}$ and $n^{*} \in \mathbb{N}$ such that $n^{*-1}<-\frac{\varepsilon}{4}$. Take $n^{* *}>n^{*}$ such that

$$
\left|\int_{0}^{1-m_{2}^{-1}} \Pi\left(a^{n^{* *}}(\theta), b^{n^{* *}}(\theta)\right) f(\theta) d \theta-\int_{0}^{1-m_{2}^{-1}} \Pi(a(\theta), b(\theta)) f(\theta) d \theta\right|<\frac{\varepsilon}{4}
$$

We have

$$
\begin{aligned}
& \int_{0}^{1} \Pi(a(\theta), b(\theta)) f(\theta) d \theta \\
\geq & \int_{0}^{1-m_{2}^{-1}} \Pi(a(\theta), b(\theta)) f(\theta) d \theta-\frac{\varepsilon}{4} \\
\geq & \int_{0}^{1-m_{2}^{-1}} \Pi\left(a^{n^{* *}}(\theta), b^{n^{* *}}(\theta)\right) f(\theta) d \theta-\frac{\varepsilon}{2} \\
\geq & \int_{0}^{1} \Pi\left(a^{n^{* *}}(\theta), b^{n^{* *}}(\theta)\right) f(\theta) d \theta-\frac{3 \varepsilon}{4} \\
\geq & \pi^{*}-n^{* *-1}-\frac{3 \varepsilon}{4} \\
> & \pi^{*}-\varepsilon
\end{aligned}
$$

which establishes (35) and completes the proof.

### 6.2 Correlation

In this appendix, we show that the result on the irrelevance of expertise regarding project quality (Proposition 1) does not rely on the independence between $\theta$ and $c$. First, we construct and example
where expertise is irrelevant even though $\theta$ and $c$ are correlated. Second, we specialize the model to $T=1$, and derive sufficient conditions for expertise to be irrelevant (therefore extending Proposition 1 to environments with correlation). Third, we show that Proposition 1 is robust to small perturbations away from independence (in the form of mixture distributions).

Consider the following example.
Example A 1 /Conditional Distribution is Mirrored Generalized Paretol Let the distribution of the safe project payoff conditional on the quality of the risky project be

$$
H(c \mid \theta)=\left(\frac{c-\underline{c}}{\bar{c}-\underline{c}}\right)^{\eta \theta}, \quad \text { where } \quad \eta>0 .
$$

Notice that the conditional distribution $H(\cdot \mid \theta)$ increases in the sense of first-order stochastic dominance as $\theta$ increases, in which case $\theta$ and $c$ are positively correlated. In this case, the conditional reverse hazard rate is $\gamma(c \mid \theta) \equiv \frac{H(c \mid \theta)}{h(c \mid \theta)}=\frac{c-\underline{c}}{\eta \bar{\theta}}$. Consider the action plan $\phi^{e}$ as described Lemma 3, after replacing the unconditional reverse hazard rate $\gamma(c)$ by its conditional counterpart $\gamma(c \mid \theta)$, and let $P^{e}(\tau)$ be the expected payments induced by the expert-investor optimal mechanism (formula 9).

Following the same reasoning as in the proof of Proposition 1, it follows that the action plan $\phi^{e}$ is implementable by a menu of linear contracts with lump-sum payments and success bonuses:

$$
a^{*}(\tau)=\frac{\Phi_{k^{*}(\tau)}(\theta)}{\eta+1} \cdot(\underline{c}-\eta \theta K) \quad \text { and } \quad b^{*}(\tau)=\triangle \cdot\left(1+\frac{1}{\eta \theta}\right)^{-1}
$$

To understand the implementability claim, note that ICS is satisfied by construction, ICR $R_{1}$ holds as $b^{*}(\tau)$ is increasing in $\theta$, and $I C R_{2}$ holds by the same argument as in the proof of Proposition 1. Because, by construction, expected payments under two-dimensional asymmetric information equal $P^{e}(\tau)$, it follows that expertise (about $\theta$ ) is irrelevant for payoffs.

The example above presents a parametric case exhibiting correlation where the result and proof technique of Proposition 1 readily apply. In what follows, we will derive sufficient conditions for expertise to be irrelevant. For tractability, we will assume that $T=1$. As in the example above, let $H(c \mid \theta)$ denote the conditional cumulative distribution of $c$ given $\theta$, let $h(c \mid \theta)=\frac{\partial H}{\partial c}(c \mid \theta)$ denote its density, and let $\gamma(c \mid \theta) \equiv \frac{H(c \mid \theta)}{h(c \mid \theta)}$ denote its associated reverse hazard rate. As in the case of independence, we assume that $H(c \mid \theta)$ is log-concave in $c$ for each $\theta$, so that $\frac{\partial \gamma}{\partial c}(c \mid \theta) \geq 0$.

From the same argument as in the text, when there is symmetric information about $\theta$, the agent experiments if $c \leq v(\theta)$, where $v(\theta)$ is the implicit solution of:

$$
\begin{equation*}
\theta \cdot \lambda \cdot \Delta-K=v(\theta)+\gamma(v(\theta) \mid \theta) \tag{36}
\end{equation*}
$$

Differentiating (36), gives

$$
\begin{equation*}
v^{\prime}(\theta)=\frac{\lambda \cdot \Delta-\frac{\partial \gamma}{\partial \theta}(v(\theta) \mid \theta)}{1+\frac{\partial \gamma}{\partial c}(v(\theta) \mid \theta)} . \tag{37}
\end{equation*}
$$

Notice that the log-concavity of $H(c \mid \theta)$ guarantees that the denominator above is positive. When there is correlation, in order to guarantee that $v^{\prime}(\theta) \geq 0$, we also need that $\frac{\partial \gamma}{\partial \theta} \leq \lambda \cdot \Delta$, which we assume from now on. This condition limits by how much an increase in $\theta$ shifts the conditional reverse hazard rate of $c$. In intuitive terms, it requires that the correlation between $\theta$ and $c$ is not too negative.

As in the case of independence, the expert-investor optimal mechanism is incentive compatible when $\theta$ is private information if and only if $v(\theta)$ is convex. When $c$ and $\theta$ are independent, we have $\frac{\partial \gamma}{\partial \theta}=0$ and, therefore, $v$ is convex if and only if $\frac{\partial \gamma}{\partial c}$ is decreasing, i.e., the reverse hazard rate is weakly concave (Condition C).

For the general case, differentiate (37) again to obtain:

$$
v^{\prime \prime}(\theta)=-\frac{\frac{\partial^{2} \gamma}{\partial \theta^{2}}(v(\theta) \mid \theta)+v^{\prime}(\theta)\left[\frac{\partial^{2} \gamma}{\partial c^{2}}(v(\theta) \mid \theta) v^{\prime}(\theta)+2 \frac{\partial^{2} \gamma}{\partial c \partial \theta}(v(\theta) \mid \theta)\right]}{1+\frac{\partial \gamma}{\partial c}(v(\theta) \mid \theta)} .
$$

Therefore, the following are sufficient conditions for expertise to be irrelevant: $\frac{\partial^{2} \gamma}{\partial c^{2}}, \frac{\partial^{2} \gamma}{\partial \theta^{2}}, \frac{\partial^{2} \gamma}{\partial \theta \partial c} \leq 0$. As such, in the case of correlation, expertise is irrelevant whenever $\gamma(c \mid \theta)$ is concave in each of its arguments and submodular.

Next, we show that our main result is robust to small perturbations away from independence.
Let $H(c)$ be a log-concave distribution with a strictly concave reverse hazard rate. Let $\Upsilon(c, \theta)$ be a joint distribution with a smooth density that is bounded away from zero in its support $[\underline{c}, \bar{c}] \times[0,1]$.

Consider the mixture distribution

$$
Q^{\alpha}(c, \theta):=\alpha H(c)+(1-\alpha) \Upsilon(c, \theta),
$$

where $0 \leq \alpha \leq 1$. As $\alpha$ approaches 1 , this distribution converges to $H$. For each $\theta$, let $c \rightarrow Q^{\alpha}(c \mid \theta)$ represent the marginal distribution associated with $\Upsilon$. Let $q(c \mid \theta)$ denote its density and $\gamma^{\alpha}(c, \theta):=$ $\frac{Q^{\alpha}(c \mid \theta)}{q^{\alpha}(c \mid \theta)}$ denote its reverse hazard rate.

For each $\alpha$, let $v(\theta, \alpha)$ denote the implicit solution of (36), and let

$$
\vartheta(\theta, \alpha) \equiv-\frac{\frac{\partial^{2} \gamma^{\alpha}}{\partial \theta^{2}}+\frac{\lambda \Delta-\frac{\partial \gamma^{\alpha}}{\partial \theta}}{1+\frac{\partial \gamma^{\alpha}}{\partial c}}\left[\frac{\partial^{2} \gamma^{\alpha}}{\partial c^{2}} \cdot \frac{\lambda \Delta-\frac{\partial \gamma^{\alpha}}{\partial \theta}}{1+\frac{\partial \partial \partial^{\alpha}}{\partial c}}+2 \frac{\partial^{2} \gamma^{\alpha}}{\partial \theta \partial c}\right]}{1+\frac{\partial \gamma^{\alpha}}{\partial c}}
$$

where we omit the $(v(\theta, \alpha), \theta)$ from all functions on the right-hand side for notational simplicity. As argued previously, expertise is irrelevant when $\vartheta(\theta, \alpha) \geq 0$ for all $\theta$ (for a fixed $\alpha$ ). We claim that there exists $\alpha^{*} \in(0,1)$ such that $\vartheta(\theta, \alpha)>0$ for all $\alpha>\alpha^{*}$. Since $(\theta, c) \rightarrow v(\theta, \alpha)$ is smooth, so is $(\theta, \alpha) \rightarrow \vartheta(\theta, \alpha)$. Moreover, by our assumption on $H, \vartheta(\theta, 1)>0$ for all $\theta$. The result then follows by uniform continuity.

## References

[1] Kannan, R. and Krueger, C. K. (1996): Advanced Analysis on the Real Line, Springer, New York.

