Online Appendix to Accompany the Paper:

MAKING THE NUMBERS? “SHORT TERMISM” & THE PUZZLE OF ONLY OCCASIONAL DISASTER

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S1- The finite horizon optimal allocation

The optimal control problem for maximizing expected performance in our problem can be written as maximizing the expected performance subject to the dynamics of the system and the budget constraint:

$$Max \int_{t=0}^{t=T} E(R)\, dt$$

Subject to:

$$\frac{dC}{dt} = e_C \rho - \frac{C}{\tau}$$

$$C(0) = C_0$$

$$\alpha + \beta = 1$$

$$0 \leq u \leq 1$$

To solve this problem we can set up the present value Hamiltonian with the co-state variable λ which represents the shadow price of the capability at any point in time. Noting that environmental shock to the earnings, *S*, has a mean of zero, does not influence system’s dynamics, and its impact is independent of the control variable (*u*), we will have $E(R) = C^{\alpha} e_R^{\beta}$, and thus we find a rather simple Hamiltonian function:

$$H(C,u,t) = C^{\alpha} e_R^{\beta} + \lambda \left(e_C \rho - \frac{C}{\tau} \right)$$

The necessary conditions for finding the optimal allocation policy, *u*, is:

$$\frac{\partial H}{\partial u} = 0$$

$$\frac{\partial H}{\partial C} = -\frac{d\lambda}{dt}$$

$$\lambda(T)C(T) = 0$$

These conditions are also sufficient because the Hamiltonian is concave with respect to *u* and *C* for feasible values of *C* and *u*. Solving the first constraint we find the following optimal allocation fraction:

$$u_{Dyn} = Min\left(1, \left(\frac{\beta}{\lambda h \rho} \right)^{\frac{1}{1-\beta}} C \right)$$

After replacing the optimum allocation in the second condition, the dynamics of co-state variable is described by the following differential equation:

$$\frac{d\lambda}{dt} = \frac{\lambda}{\tau} - (1-\beta) \left(\frac{\beta}{\lambda h \rho} \right)^{\frac{\beta}{1-\beta}}$$

Solving this differential equation (using Bernoulli method) we get the following time trajectory for the shadow price of capability, λ:

$$\lambda(t) = \left(\frac{\tau(1-\beta)}{\left(\frac{h\rho}{\beta} \right)^{\frac{\beta}{1-\beta}}} + K e^{\frac{t}{\tau(1-\beta)}} \right)^{1-\beta}$$

Using the end state condition (λ(T)=0) we can solve for the constant K which gives the analytical expression for the time trajectory of λ for any time horizon and combination of parameters.

$$K = \frac{-\tau(1-\beta)}{\left(\frac{h\rho}{\beta} \right)^{\frac{\beta}{1-\beta}} e^{\frac{T}{\tau(1-\beta)}}}$$

Inspecting the results, we note that this constant term is negative, and very small as long as T>τ(1-β), that is, the time to end of horizon is appreciably smaller than the time constant for the erosion of capability. Therefore, λ is almost constant until we get fairly close (relative to τ) to the end of investment horizon (T), at which time the shadow price starts to decline precipitously (note the exponential term in equation for λ), leading to increasing allocation of resources to performance generation and a decline of capability, until at exactly time T the shadow price and capability stocks both become zero.

Therefore, assuming T>τ(1-β), we can find a constant shadow price of capability that applies to a large section of our time horizon:

$$\frac{d\lambda}{dt} = 0 \Rightarrow \lambda = \left(\frac{\tau(1-\beta)}{\left(\frac{h\rho}{\beta}\right)^{\frac{\beta}{1-\beta}}} \right)^{1-\beta}$$

Replacing λ with this steady-state value in equation for u_{Dyn} and simplifying the equations we get the following expression for the approximate optimal control allocation:

$$u = Min\left(1, u^* \frac{C}{C^*}\right)$$

This simple expression suggests that optimal allocation in the dynamics case is 1) consistent with the steady state allocation, that is, if capability is at the steady-state optimal level, the allocation will be the same as steady state. 2) Variations of the optimal path in capability are compensated for by linear shifts in the allocation fraction: when capability falls short of the optimal steady state value, the allocation favors capability investment, while too much capability (relative to steady state) will lead to more effort (than steady state optimal) being allocated to earnings generation. Note that the heuristic used in our paper simplifies to this function when γ =0.

S2-The infinite horizon optimal allocation

The infinite horizon optimal control problem with discounted performance can be written as:

$$Max \int_{t=0}^{t=\infty} e^{-rt} E(R)\, dt$$

Subject to:

$$\frac{dC}{dt} = e_C \rho - \frac{C}{\tau}$$

$$C(0) = C_0$$

$$\alpha + \beta = 1$$

$$0 \leq u \leq 1$$

Here *r* is the continuous time discount rate. To solve this problem we set up the current value Hamiltonian with the transformed co-state variable ψ and follow the regular steps:

$$H(C, u, t) = C^{\alpha} e_R^{\beta} + \psi \left(e_C \rho - \frac{C}{\tau} \right)$$

To find the optimal allocation policy, *u*, we solve the following equations:

$$\frac{\partial H}{\partial u} = 0$$

$$\frac{\partial H}{\partial C} = -\frac{d\psi}{dt} + r\psi$$

$$\lim_{T\to\infty} e^{-rt}\lambda(T) \geq 0, \lim_{T\to\infty} e^{-rt}\psi(T)C(T) = 0$$

Solving the first constraint, we find the following optimal allocation fraction which is similar to the finite horizon case:

$$u_{Dyn} = Min\left(1, \left(\frac{\beta}{\psi h \rho}\right)^{\frac{1}{1-\beta}} C \right)$$

After replacing the optimum allocation in the second condition, the dynamics of co-state variable is described by the following equation:

$$\frac{d\psi}{dt} = \psi(r + \frac{1}{\tau}) - (1-\beta)\left(\frac{\beta}{\psi h\rho}\right)^{\frac{\beta}{1-\beta}}$$

In this case, we observe that the equilibrium ψ value satisfies the terminal conditions and thus provides the following solutions for the optimal co-state trajectory and allocation:

$$\frac{d\psi}{dt} = 0 \Rightarrow \psi = \left(\frac{\tau(1-\beta)}{(1+r\tau)\left(\frac{h\rho}{\beta}\right)^{\frac{\beta}{1-\beta}}}\right)^{1-\beta}$$

$$u = Min\left(1, u^* \frac{C}{C^*}(1+r\tau)\right)$$

In the infinite horizon discounted case the optimal allocation differs from the finite horizon, undiscounted, case with a factor of (1+rτ): if capabilities are slow to erode (large τ) and if discount rate is high, the baseline allocation favors earnings generation beyond the steady state optimal allocation. Moreover, the infinite horizon case does not include the precipitous decline in the value of capability at the end of time horizon (because there is no end to the time horizon).

S3- The effort allocation function and characteristic of the resulting phase diagram

Variables and model definition (reproduced from the paper)

Performance Function:	$R = C^\alpha e_R^\beta + S$
Allocated effort to performance	$e_R = uh$
Allocated effort to capability	$e_C = (1-u)h$
System's dynamics	$\frac{dC}{dt} = e_C\rho - \frac{C}{\tau}$
Optimal steady-state allocation policy	$u^* = \frac{\beta}{\alpha+\beta}$

Allocation heuristic used in this study $u = Min\left(1, u^*\left(\frac{R^T}{R_{u^*}}\right)^\gamma \left(\frac{C}{C^*}\right)^{1-\gamma\beta}\right)$

Target performance $R^T = {C^*}^\alpha {e_R^*}^\beta$

Expected performance using optimal steady state policy $R_{u^*} = C^\alpha {e_R^*}^\beta + S$

Effort to performance under optimal steady state policy $e_R^* = u^* h$

Capability using optimal steady state policy $C^* = (1-u^*)h\rho\tau$

Throughout the rest of the document, it is assumed that we are using a constant return to scale production function (α+β=1).

Phase diagram

The phase diagram for the system reflects the changes in capability (dC/dt) as a function of capability. Specifically, replacing the equation for allocation into the system's dynamics, we get:

$$\frac{dC}{dt} = (1-u)h\rho - \frac{C}{\tau} = \left(1 - Min\left(1, u^*\left(\frac{R^T}{R_{u^*}}\right)^\gamma \left(\frac{C}{C^*}\right)^{1-\gamma\beta}\right)\right)h\rho - \frac{C}{\tau}$$

after replacement and simplification, we get:

$$\dot{C} = \frac{dC}{dt} = h\rho\left(1 - Min\left(1, \frac{u^* {C^*}^{\gamma-1}}{(C^\alpha {e^*}_R{}^{1-\alpha} + S)^\gamma C^{\gamma-\gamma\alpha-1}}\right)\right) - \frac{C}{\tau}$$

The allocation function thus responds to the capability level and to environmental shocks. The latter component reduces variability in response to the environmental shocks and the former either smoothes earnings (γ>1) or fixes capability shortfalls (γ<1) in response to deviations of capability. The response to capability level is thus the result of two competing forces, one which attempts to align the capability level with the optimal trajectory based on the optimal control policy, and another which compensates for falling capability by increasing allocation to earnings generation, thus smoothing the earnings trajectory. These forces are at balance when γ=1, capability renewal tendencies win for smaller γ and earnings smoothing dominates for $\gamma \geq 1$.

For simplifying the analysis of the system, we focus on the deterministic version of the equation, where the impact of environmental noise is excluded from calculations of capability change:

$$\dot{C} = h\rho\left(1 - Min\left(1, u^*\left(\frac{C}{C^*}\right)^{1-\gamma}\right)\right) - \frac{C}{\tau}$$

By equating this equation to zero, we find that it always has a fixed point at C^* where capability equals the optimal steady state capability. The existence and number of other fixed points depends on γ.

1) $\gamma \leq 1$:

For $0 \leq C \leq C^*$ we have:

$$\dot{C} = h\rho\left(1 - u^*\left(\frac{C}{C^*}\right)^{1-\gamma}\right) - \frac{C}{\tau} \geq h\rho(1 - u^*) - \frac{C^*}{\tau}$$

Yet the right-hand side of inequality is by definition zero, so $\dot{C} \geq 0$.

Using a similar argument, it is easy to see that for $C \geq C^*$ the net rate of change in capability is always negative. Therefore for $\gamma \leq 1$ the phase diagram includes a single equilibrium at C^* and no other fixed points, the system will always move back towards this equilibrium.

2) $\gamma > 1$:

Calling $C^*\left(\frac{1}{u^*}\right)^{\frac{1}{1-\gamma}} = C^s$, the net flow equation has two ranges:

$$\dot{C} = -\frac{C}{\tau} \quad if \quad C < C^s$$
$$\dot{C} = h\rho\left(1 - u^*\left(\frac{C}{C^*}\right)^{1-\gamma}\right) - \frac{C}{\tau} \quad if \quad C \geq C^s$$

Therefore, at least one additional fixed point exists at C=0. We now focus on the behavior of $\dot{C}$ when $C \geq C^s$.

First, we observe that $\dot{C}$ is a continuous function in C that at C^s takes the $-\frac{C}{\tau}$ value and at C^* is zero. The extremum for $\dot{C}$ can be found by equating its derivative with respect to C to zero which provides the following unique solution:

$$\frac{\partial \dot{C}}{\partial C} = 0 \Rightarrow C = \left((\gamma - 1)h\rho\tau {C^*}^{\gamma-1}\right)^{\frac{1}{\gamma}}$$

On the other hand:

$$\frac{\partial^2 \dot{C}}{\partial C^2} = -(\gamma - 1)\gamma r u^* {C^*}^{\gamma-1} C^{-\gamma-1}$$

All the terms in the equation are positive, except for the one negative sign, therefore, the second derivative of capability flow with respect to capability is always negative in this region. As a result, the extremum found above is the only maximum for the net capability flow function which should be above zero (given that $\dot{C} = 0$ at C^*) and thus there is a single other point at which $\dot{C} = 0$. This point can be found numerically[1] by solving the rate-level equation for zero capability change rate. Given the positive first derivative of $\dot{C}$ with respect to C at this point, it is also the only tipping point for the system.

To recap, when $\gamma \leq 1$, the system includes a single unique equilibrium at $C = C^*$. For $\gamma > 1$ the system includes exactly three fixed points: two are stable equilibria at $C = 0,\ C = C^*$ and one is a tipping point located in between.

S4- Performance of surviving firms in large sample experiments

Figure S 1 reports the results of large sample experiments where performance of surviving firms are graphed as a function of earnings focus and parameters of environmental uncertainty. In panel a, variations with increasing standard deviation of demand variability are shown while fixing the correlation

[1] No general analytical solution exists for the location of tipping point.

time at 12 months. In panel b, noise correlation time is varied, fixing the standard deviation of environmental shocks at 10% of optimal performance. In both cases earnings of surviving firms increase in expectation as γ increases, because the increase in γ leads to an increasingly lucky sample of surviving firms. At very high levels of γ the effect reverses because extremely earnings focused firms, even if very lucky, by over investing in capabilities ensure that their performance does not exceed market expectations, and thus do not show higher performance.

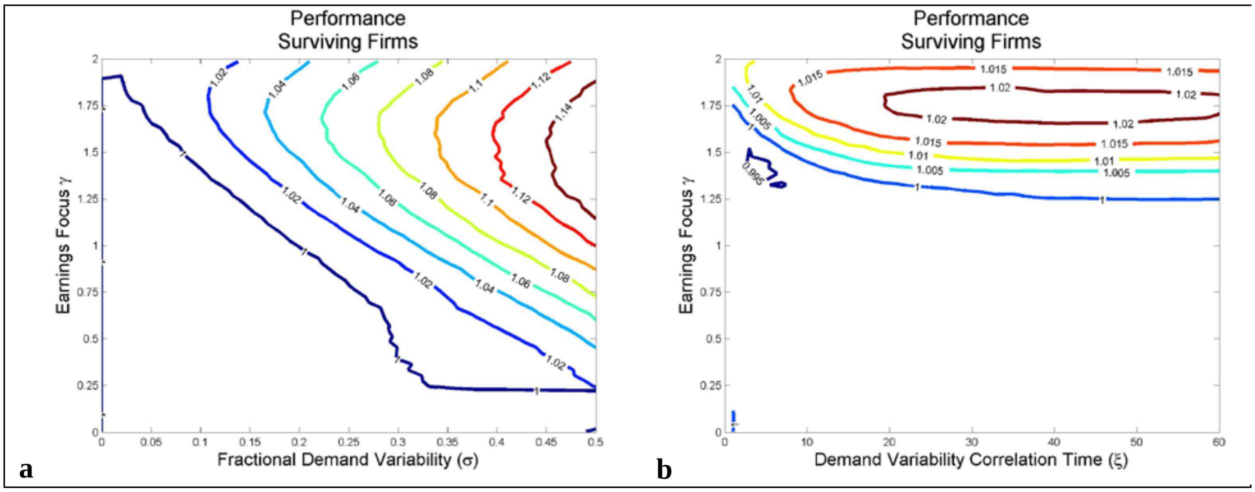

Figure S 1- Performance of surviving firms as a function of earnings focus and a) Environmental variability b) Correlation time of that variability

S5- Time compression diseconomies in capability investments

We incorporate time compression diseconomies by using the following equation for the capability dynamics:

$$\frac{dC}{dt} = e_C{}^*(\frac{e_C}{e_C{}^*})^{(1-\delta)}\rho - \frac{C}{\tau}$$

Here $e_C{}^* = (1 - u^*)h$ is the amount of effort allocated to capability building under optimum steady-state allocation policy, and δ is the time compression diseconomy parameter. With δ =0, we get to the base model, and with δ=1, capability growth rate will always be equal to the optimum value regardless of the actual effort allocated to capability building.

Figure S 2 reports the resulting fraction of firms that fail (panel a) and performance variability under different levels of time compression diseconomies (and earnings focus). In general time, compression diseconomies do reduce tipping and failure rates, but only modestly, requiring very high values of δ (~1) to fully remove tipping dynamics. Impact on performance variability is negligible.

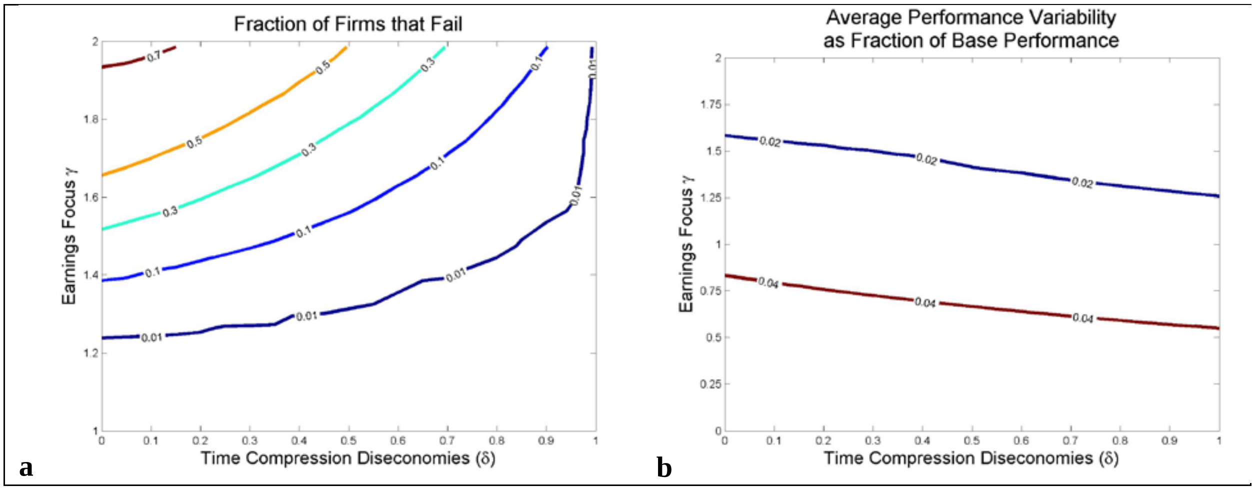

Figure S 2- Impact of time compression diseconomies on tipping dynamics.

S6- Nonlinear capability erosion rates

We incorporate potential nonlinearity in capability erosion rates using the following equation for the capability dynamics:

$$\frac{dC}{dt} = e_C\rho - \frac{C^*}{\tau}(\frac{C}{C^*})^\kappa$$

With this setting, κ=1 recreates our base model, and κ values above one lead to lower erosion rates for capability values below C* and higher erosion rates above optimum capability. In Figure S 3 we report the large-scale results where we change κ between 1 and 2 and earnings focus between 0 and 2. Results show a modest reduction in failure rates with increases in κ, though within realistic ranges the tipping dynamics persist, and there is limited impact on performance variability.

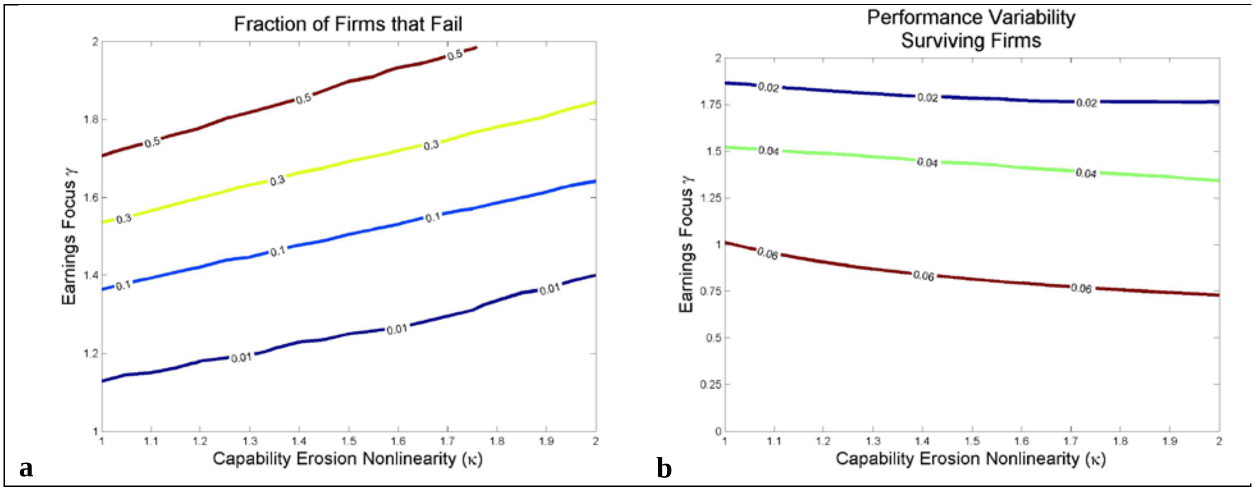

Figure S 3- Impact of nonlinearity in capability erosion rates on firm failure and performance variability among surviving firms.

S7- Asymmetric earnings management

We incorporate potential asymmetries in earnings management using the following equation for managerial decision rule:

$$u(S,C) = \begin{cases} Min\left(1, u^*\left(\frac{R(u^*,0,C^*)}{R(u^*,S,C)}\right)^{\gamma}\left(\frac{C}{C^*}\right)^{1-\gamma\beta}\right) & if\ R(u^*,0,C^*) > R(u^*,S,C) \\ Min\left(1, u^*\left(\frac{R(u^*,0,C^*)}{R(u^*,S,C)}\right)^{\gamma(1-\zeta)}\left(\frac{C}{C^*}\right)^{1-\gamma\beta}\right) & if\ R(u^*,0,C^*) \leq R(u^*,S,C) \end{cases}$$

By changing ζ values between 0 and 1, we can create asymmetric responses where, foreseeing earnings to exceed targets, managers may or may not over-invest in capabilities. Specifically, with ζ=1 we get the base case model and with ζ=0 we have no adjustment of capability investment based on expected excess earnings. Figure S 4 reports on the failure rates for different values of ζ, showing significant robustness of the results to this behavioral assumption.

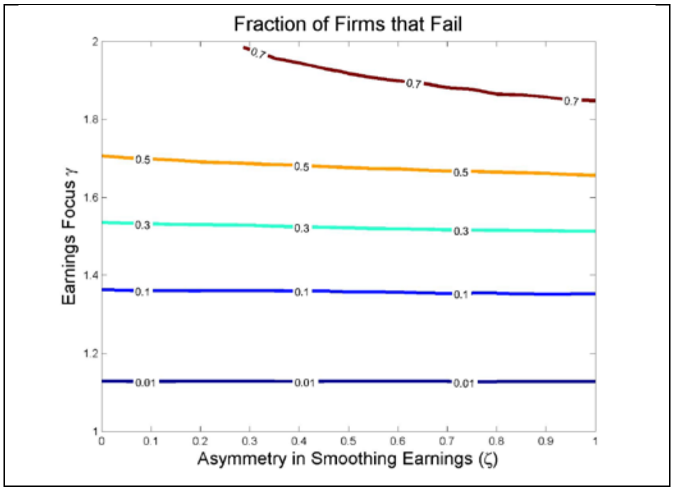

Figure S 4- Impact of asymmetric earnings management heuristics.

S8- Endogenous effort growth

We incorporate the possibility of endogenous effort growth through the following equation:

$$\frac{dh}{dt} = (R\left(\frac{h(0)}{R^*(0)}\right)Max(0{,}1.2 - \chi V) - h)/\theta$$

Here $\frac{h(0)}{R^*(0)}$ becomes a constant term that reflects the rates by which performance translate into future effort availability. The χ parameter regulates the penalty imposed due to variability of earnings, V (measured as mean absolute fractional error between the actual performance and market targets). The time constant θ represents the time it takes for impact of performance on available effort to materialize (due to various perception and physical delays) and a value of 12 month is used in the simulations. The equation is formulated to reflect a 20% per year maximum growth rate, and results are similar, but more pronounced, for higher growth rates. We start the effort from the initial value in the base model (h(0)=200) and allow it to dynamically change in the rest of the simulation time. Large-scale results are reported in Figure S 5. While the fraction of firms that fail do not change considerably (tipping dynamics are robust to endogenizing h), more significant performance variation is observed in this setting due to endogenous growth of lucky firms, sampled due to failure of unlucky ones, among the more earnings-focused firms. This effect becomes stronger when market puts a penalty on volatility of performance

(Panel b). However, once the full sample of firms is considered, short-termism leads to both lower performance average and higher variability.

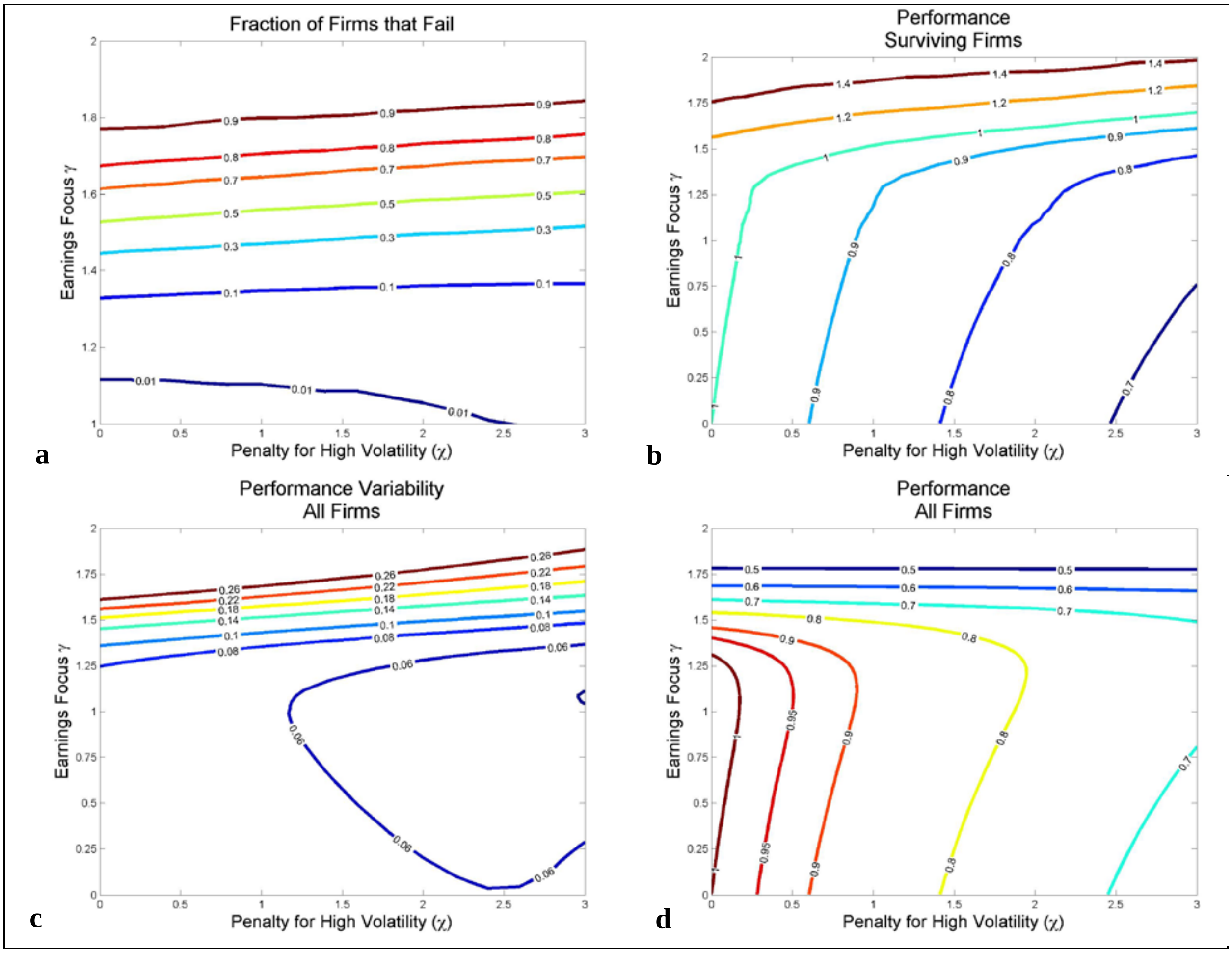

Figure S 5- Impact of endogenous effort on firm failure (a) performance of surviving firms (b), variability in performance across all firms (c) and performance for all firms (d).