Supplementary material to accompany:

Impact of growth opportunity and competition on dynamics of capability development

Table of content:

S1- Dynamic capabilities vs. ad-hoc problem solving

In this part of the e-companion we show how for the general firm formulation discussed in the paper only three shapes of relationship between steady-state performance and allocation policy (discussed in figure 1 in the paper) exist.

The system of differential equations describing capability dynamics (equations 1-10 in the paper) can be summarized as:

$$\frac{dC_O}{dt} = R.(1-f).Max(e_{ah}, g(C_D)) - \frac{C_O}{d_O} \qquad \text{(S1)}$$

$$\frac{dC_D}{dt} = R.f.e_D - \frac{C_D}{d_D} \qquad \text{(S2)}$$

C_D is independent of C_O and linear and dynamic with respect to C_D. Therefore assuming fixed effort (R) and allocation policy (f) the solution for C_D can be obtained in closed form as:

$$C_D(t) = (C_{D,Initial} - R.f.e_D.d_D).\exp^{-t/d_D} + R.f.e_D.d_D \qquad \text{(S3)}$$

While derivation of specific dynamics of C_O depends on the functional form of *g(.)*, we note that the only feedback loops in the system are the two balancing loops governing the depreciation of capabilities, which are both first order. Therefore the system will ultimately reach equilibrium in the value of both capabilities. We can therefore calculate the steady state value of both capabilities with respect to the organizational investment policy parameter, *f*, using Little's law (Little 1961). From equation S3, the steady state value of C_D is $R..f.e_D.d_D$. Replacing this value in equation S1 and solving for steady state value of operational capability we find:

$$C_{O,eq} = R.(1-f).Max(e_{ah}, g(R.f.e_D.d_D)).d_O \quad \text{(S4)}$$

And therefore steady-state firm performance can be found as a function of firm's policy for investment in different types of capability:

$$\Pi_{eq} = \begin{cases} p.R.d_O.e_{ah}.(1-f) - R - c & e_{ah} > g(R.f.e_D.d_D) \\ p.R.d_O.g(R.f.e_D.d_D).(1-f) - R - c & e_{ah} \le g(R.f.e_D.d_D) \end{cases} \quad \text{(S5)}$$

Now we can analyze the behavior of this performance function with respect to the policy parameter, *f*:

Call the second expression in equation S5 (when $e_{ah} \le g(R.f.d_D)$) *A*. Note that:

$$\frac{d\Pi_{eq}}{df} = \begin{cases} -p.R.d_O.e_{ah} & e_{ah} > g(R.f.d_D) \\ p.R.d_O.[\frac{dg(R.f.e_D.d_D)}{df}.(1-f) - g(R.f.e_D.d_D)] & e_{ah} \le g(R.f.d_D) \end{cases} \quad \text{(S6)}$$

The first part of derivative (for $e_{ah} > g(R.f.e_D.d_D)$) is a constant negative, therefore there is only a single peak at f=0 for this part of the function. For expression A the slope equals $p.R.d_O.g'(0)$ at f=0 which is positive. Moreover, the slope of performance with respect to *f* becomes negative at f=1. Therefore at least one local peak exists between f=0 and f=1. Taking the second derivative of A with respect to *f* we observe that this derivative remains non-positive for all values of *f* between 0 and 1. Therefore assuming a continuous and differentiable *g(.)* function there is only one peak performance for A with respect to *f*. Combining the overall shape for A with that of performance with ad-hoc efficiency, we obtain the three possibilities of performance as a function of *f* discussed in the paper.

S2- Simulation Parameters

Table S1 reports the parameter values used for the simulations reported in the paper and in the e-companion. Sensitivity analysis to important assumptions of the model are reported in the paper with corresponding alternative parameters in the table below.

Table S1- The parameters of the model used in simulation experiments reported in the paper and the e-companion.

Parameter	Value	Units	Definition
C	2000	K$/Month	The costs of firm operations other than the investments in capability building.
c_{CD}	5	K$/DC/Month	The monthly unit cost of maintaining dynamic capabilities.

d_O	10	Month	The average life of operational capabilities.
D_D	10	Month	The average life of dynamic capabilities.
e_{ah}	2.5	OC/K$	The efficiency of ad hoc processes for creating operational capabilities.
e_D	0.01	DC/K$	The efficiency of ad-hoc processes in creation of dynamic capabilities.
P	0.15	K$/Month/OC	The productivity of operational capabilities expressed in terms of thousands of dollar per month of performance created by each unit of operational capability
R	1000	K$/Month	Total investment in development of new capabilities (zero and dynamic).
g(x)	1.2*LN(x)		The function relating dynamic capability to efficiency in building operational capabilities.
MaxEff	5	OC/K$	The maximum efficiency feasible in development of dynamic capabilities.
Ω	0.5	Dimensionless	Return on scale parameter.
C_{ON}	50000	OC	Normal operational capability
υ	0.5	Dimensionless	Time compression diseconomy factor.
R_N	3000	K$	Normal investment in capabilities
K	30	K$/Month	The scaling factor for production function in the first alternative model
e_{adhoc}	100	Dimensionless	The efficiency of adhoc problem solving for doing the main production activities of the firm.
e_C	0.02	C/K$	The efficiency of building capabilities in the first alternative model
d_C	50	Month	The average life of capabilities in the first alternative model.
A	0.25	Dimensionless	The Cobb-Douglas production function coefficient for capabilities
M_p	0.004	K$/OC/Month^2	The scaling parameter for determining productivity change rate based on level of capability.
e_O	5	OC/K$	The efficiency of investment in operational capabilities is a constant in the second alternative formulation.
e_{ahp}	2.5	Dimensionless	The efficiency of ah-hoc problem solving for increasing the

			productivity of operational capabilities.
h(x)	1.2*LN (x)		The function relating dynamic capability to productivity increase rate in the second alternative formulation.
T_B	30	Month	The slack life time.
d_p	10	Month	The productivity erosion time.

S3- Worse-before-better learning traps with fixed effort

In this part we show the worse-before-better dynamics and how they lead to learning traps. Consider the comparison between two firms. Firm *a* is spending 15% of its investment resources on dynamic capabilities while firm *b* is spending 35%. Both firms are achieving similar performances because they are on similar levels on the two sides of the performance peak (see Figure **S1**-B). Here the maximum equilibrium performance is attained by spending 24% of resources on dynamic capabilities. Now the managers in both firms decide to experiment with changing their investment in dynamic capabilities (10% increase/decrease for *a* and *b* respectively) to see if different investments in dynamic capabilities are warranted. Figure S1-A describes the performance observed by the two firms with parameters described in Table S1. Initially firm *a* observes a drop in its performance as the investment is diverted from operational capability and the stock of these capabilities depletes faster than it is recovered through investment. However, the buildup of the dynamic capability gradually increases the efficiency of the investments made in the operational capability and leads to recovery of performance. The firm gets back to its initial performance after about 20 months and continues to enjoy improvements in performance as it moves towards a new performance equilibrium.

Firm b experiences a sharp increase in performance as a result of increasing the investment in operational capabilities. The reason is that larger investment in operational capabilities pays off very well at the beginning, given the initially high level of dynamic capabilities. After a few months however, the initial sharp increase in performance is followed with a slow decline as dynamic capabilities are eroded and the return on investment in operational ones decline. Nevertheless, the experiment results in an overall performance improvement similar to firm *a*.

Even though the start and the end points of the experiments are very similar in terms of performance, the lessons learned may be very different. In firm *a* managers can call the experiment a success only if three conditions are satisfied: 1)they have a good understanding of delays involved in building the dynamic capabilities and seeing their benefits, 2) they have long-enough a planning horizon in their position to by-pass the initial dip in the performance, 3) they have the political will and influence to rally the rest of the organization to sustain investment in dynamic capabilities for long enough a period to observe the benefits. However, it is more likely that the managers under-estimate delays involved in building dynamic capabilities, do not expect to remain in their current position for long enough to benefit from their initial performance sacrifice, or they can not convince the rest of the organization to sustain the experiment for long enough. Under any of these conditions the experiment is abandoned prematurely and further investment in dynamic capabilities is discouraged.

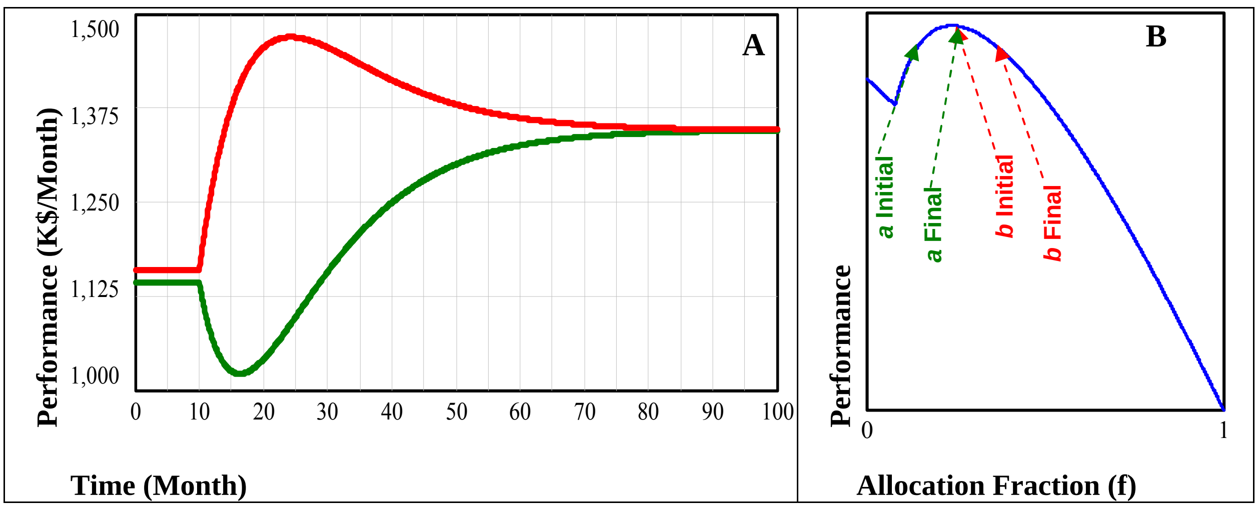


Figure S1- Performance dynamics in shifting investment from zero to dynamic capabilities. Starting from investment of 15% of resources in dynamic capabilities, firm a, in green, increases this amount to 25% at time 10 and experiences a temporary drop in performance before experiencing the improvement. Firm b, in red, starts from 35% and moves to 25% at time 10. It experiences a significant improvement before stabilizing at final level. Left: The steady state performance as a function of f. The start point and finish points are highlighted for the two firms.

In contrast, the managers in firm b are likely to be rewarded for significant improvement in the firm performance through cutting unnecessary costs and focusing on the core business processes. The slow decline of performance after the sharp initial increase may get less attention or be associated with other potential reasons which are closer in time than a change over a year ago. As a result of this experiment the policy of cutting down the dynamic capabilities receives a strong reinforcement and is more probable to be pursued further.

S4- Process for finding Nash equilibrium in games

In section 2 of the paper we report the game theoretic equilibrium for a competition between 10 firms under different firm and market parameterizations. Given the relatively complex model structure, the Nash equilibrium was not analytically derived. Instead, we followed an iterative procedure to numerically find the Nash equilibrium in each setting. The procedure includes the following steps:

1) Start with L (in this case L=10) identical firms in a market. L-1 firms are distributed on the strategy space (choosing different values of *f)*.
    a. In the first round the L-1 firms are uniformly distributed on the strategy space.
    b. In the next rounds they are increasingly closer to the winning strategy in the last iteration. We divided the feasible space to half its prior-iteration's length in each new iteration. Other sizes for feasible space in each iteration (step lengths) could be used. In fact a zero step size (all firms selecting the optimum strategy for the last iteration) often worked fine, though in average requiring a few more iterations.
2) Optimize the performance of the Lth firm using a non-linear optimization algorithm by changing its allocation policy, *f,* between 0 and 1. Objective function is to maximize the final performance (∏) at the 100th month of competition for the Lth firm. Report f_{optim} (the winning policy in this iteration).
3) If the remaining feasible space is smaller than 0.001 (any other arbitrary small number could be used) and the optimum *f* in the last step is between the lowest and highest competing allocation policy among the other firms, then algorithm has converged, otherwise, go to step 1 and start a new iteration.
4) Once the algorithm has converged, test it by putting all of the L-1 firms to have $f= f_{optim}$. Then repeat step 2 for the Lth firm and confirm that the f_{optim} does not change.

If this procedure converges to a f_{optim} value for the Lth firm, this value will be the Nash equilibrium for the game: given the symmetric structure of the firms, each firm's best policy is to stay at f_{optim} if everybody else is playing that (otherwise the optimization for the firm L in step 4 would have revealed a profitable deviation).

The procedure indeed converged to a single f_{optim} for all of the cases we analyzed in the paper. However, one of the limitations of the procedure is that it does not inform the uniqueness of the equilibrium and thus the possibility of the existence of mixed strategy equilibriums.

S5- Different returns on capabilities

In the paper we analyze two different scenarios in which the returns on different types of capabilities where changed (section 3-1). We first discuss the saturation in the efficiency of investment in operational capabilities that can limit the usefulness of dynamic capabilities for building those operational capabilities.

We test the impact of this alternative assumption by putting a maximum level on the efficiency of investments in operational capabilities. Specifically, we modify equation 8 as follows to represent how dynamic capabilities impact the efficiency of investment in operational ones:

$$e_O = Max(e_{ah}, Min(MaxEff, g(C_D))) \quad \text{(S7)}$$

Here *MaxEff* represents the maximum feasible efficiency for building operational capabilities. A value of 5 is used in the simulation experiments reported Figure S2 reports the detailed results in this case.

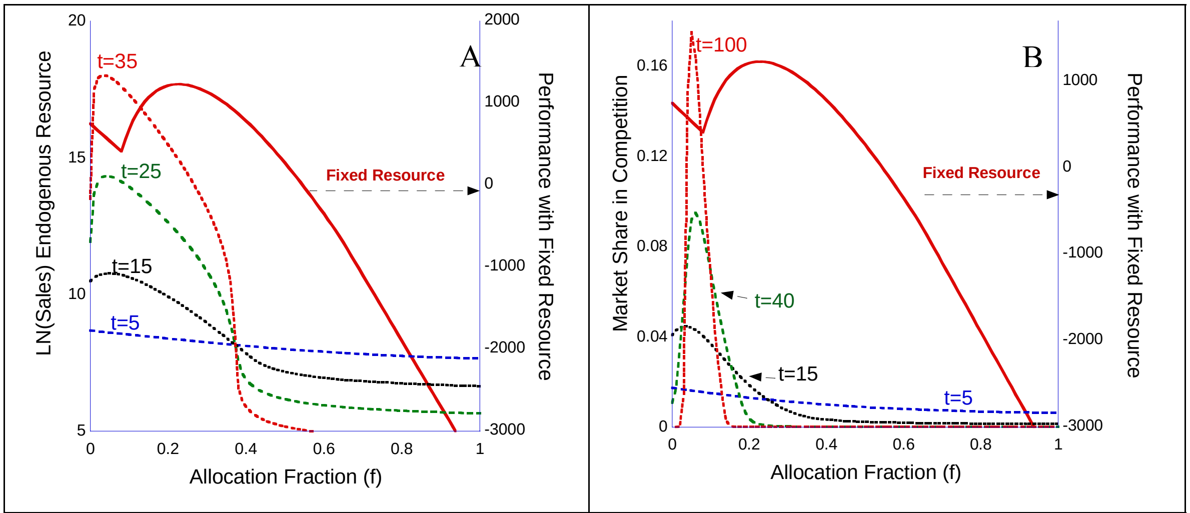


Figure S2– The result of analysis when efficiency of investment in operational capabilities saturates and therefore large amounts of dynamic capabilities are not beneficial. Different resource allocation policies are compared at different times for both endogenous effort and competition cases. A) Results for the case with endogenous effort (left axis) is compared to existence of fixed effort levels to invest (right axis). B) The results for the case with 101 firms competing with different levels of allocation fraction, *f*, is compared to the exogenous effort case. The dominant strategy in a strategic game is to invest no resources in dynamic capabilities (*f*=0).

The second set of analysis reported in the paper concerns firms with decreasing returns to scale operational capabilities. Equation 12 in the paper specifies the formulation change for this analysis and Table S1 reports the parameter values. Figure S3 discusses the detailed results including the behavior under fixed and endogenous effort, as well as under competition.

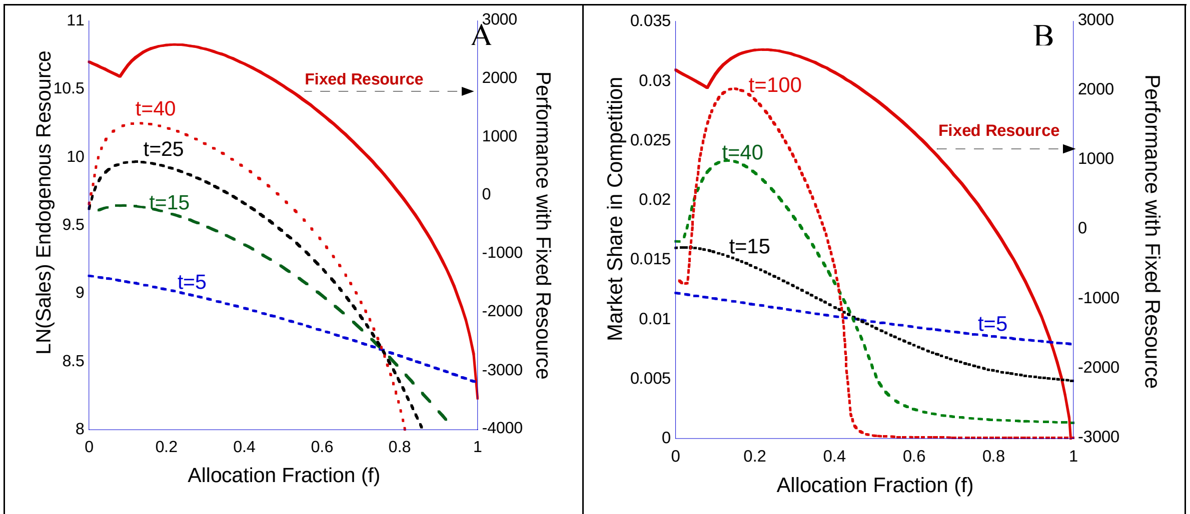


Figure S3– The result of analysis when firms are governed by decreasing return to scale. The decreasing return reduces the speed of growth and limits it, thus enabling investment in longer-term policies. Different resource allocation policies are compared at different times for both endogenous effort and competition cases. A) Results for the case with endogenous effort (left axis) is compared to existence of fixed effort levels to invest (right axis). Peak performance is at f=0.13 for endogenous effort. B) The results for the case with 101 firms competing with different levels of allocation fraction, f, is compared to the exogenous effort case. The firm with f=0.15 wins the competition. The game theoretic policy of f=0 dominates other policies if firms are picking their allocation policy strategically.

S6- Alternative model formulations

Two alterative formulations for the firm structure are examined. The first alternative formulation is derived from the Cobb-Douglas production function widely used in economics. We further simplify the formulations by focusing on the allocation of organizational resources between production and the development of capabilities and resources that contribute to production. Therefore only a single stock variable, which we call capability (C), is present. We conceptualize firm's (potential) output to be a constant return to scale Cobb-Douglas function of the firm's efforts allocated to production and the current level of capability. Ad-hoc problem solving can be used instead of the capability for producing output. Equations 1-6 are replaced with the following:

$$\Pi = K.C^{\alpha}.Max(R_O, e_{adhoc})^{1-\alpha} - R - c \quad \text{(S8)}$$

$$\frac{dC}{dt} = R_C.e_C - \frac{C}{d_C} \quad \text{(S9)}$$

$$R_O = R.(1-f) \quad \text{(S10)}$$

$$R_C = R.f \quad \text{(S11)}$$

Here K is a constant, e_{adhoc} is the efficiency of ad hoc problem solving for doing the main production activities, and α is the Cobb-Douglas function exponent for the impact of capability on production. e_C and d_C are the efficiency of investment in, and the average life of, the capability (similar to the same concepts for operational and dynamic capabilities in the base model). With endogenous effort, a one month delay is introduced between revenue generation and investment. The delay avoids a circular logic in defining and calculating the variables going from performance to effort available and back to performance.

Given the Cobb-Douglas component of α=0.25, the optimum long-term allocation policy with fixed effort is f=0.25. Here the capability directly contributes to the payoff (See equation 21) and therefore reducing the investment in it is more harmful than the base case. Nevertheless, we observe a shift to f=0.22 in the most productive strategy when we consider endogeneity of available effort. Over the long-term, in the competitive market with 101 firms, the dynamics favor the firm with f=0.22 as well. Similar to the base case scenario the winning strategy shifts towards lower investment in the capability if we consider shorter time horizons (or include a discount rate, which we did not discuss here). Interestingly, the game theoretic equilibrium for ten competing firms is to invest no effort in capability building (f=0), following a similar logic as in the base case. Figure S4 discusses the detailed results for the analysis of capability dynamics and firm performance under this new formulation.

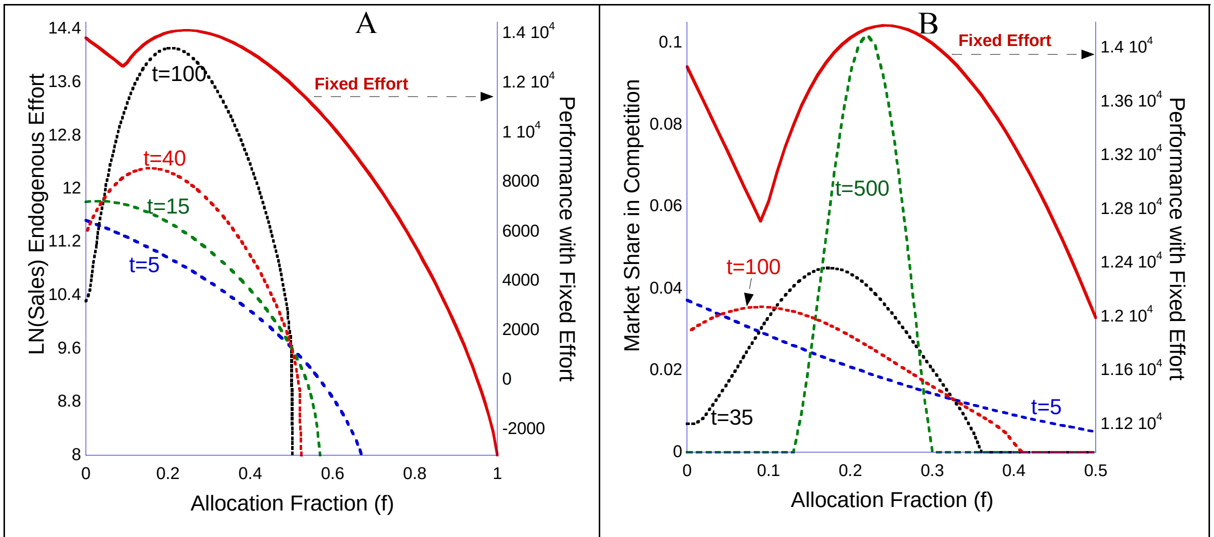


Figure S4– The result of analysis for the first alternative model, with Cobb-Douglas production function. Direct contribution of capability in the production and the constant return to scale function tend to increase the value of investment in capability in the presence of endogenous effort and competition. Different resource allocation policies are compared at different times for both endogenous effort and competition cases. A) Results for the case with endogenous effort (left axis) is compared to existence of fixed effort levels to invest (right axis). Peak performance is at *f*=0.22 for endogenous effort, compared to 0.25 for fixed effort. B) The results for the case with 101 firms competing with different levels of allocation fraction, *f*, is compared to the fixed effort case. The firm with *f*=0.22 wins the competition. However, the game theoretic policy of *f*=0 is still the Nash equilibrium.

The second alternative firm formulation is based on the realization that many dynamic capabilities do not directly impact the rate of change in an operational capability, rather, they impact the productivity of an operational capability. For example human resource training capability (a dynamic capability) improves the productivity of the sales force (an operational capability) but does not directly increase or decrease the sales force. Process improvement (dynamic capability) often improves the productivity of manufacturing (operational capability) and alliance formation process (dynamic capability) can help with the productivity of marketing or production (operational capabilities).

We therefore formulate an alternative firm structure in which dynamic capabilities contribute to increasing the productivity of the operational capability, and not the operational capability itself. As a result e_O becomes a constant and the following equation is added to the equations 1-6:

$$\frac{dp}{dt} = M_p.Max(e_{ahp}, h(C_D)) - \frac{p}{d_p} \qquad \text{(S12)}$$

Here p is the productivity of the operational capabilities (see equation 1), M_p is a constant, e_{ahp} is the effectiveness of ad hoc problem solving for increasing the productivity and *h(.)* is the function specifying how dynamic capabilities (C_D) impact productivity and resembles *g(.)*. The erosion of productivity through turnover, entropy, and depreciation is captured by p/d_p term. Table S1 provides the parameter values. Full models are available from the author's website.

The results of this analysis are very similar to the base case. Maximum performance with fixed resources is achieved at f=0.23. The consideration of the endogeneity of effort moves the efficient resource allocation to f=0.07, and the firm with f=0.08 wins the uniform competition among 101 firms. Similar to the base case, the dominant strategy for strategic competition is to invest no effort in the dynamic capabilities (f=0).

In this formulation the impact of dynamic capabilities on the firm's performance goes through a stock variable, productivity. This fact underlies the similarity of the results in this section with those in the base case. When effort availability is tied to the current performance of the firm, investment in operational capability gets a premium over dynamic capabilities. Those investments activates the reinforcing loop of investment-performance-effort availability, leading to provision of more total available effort, compared to investment in dynamic capabilities that contribute to the loop more slowly. In competitive markets, the firms that grow their potential output faster gain market share over the slow-moving firms. Consequently, the winning firm in competitive market invests much less in long-term capabilities, and if selecting its allocation policy strategically, would converge to f=0. Figure S5 reports the detailed results for the analysis under this formulation.

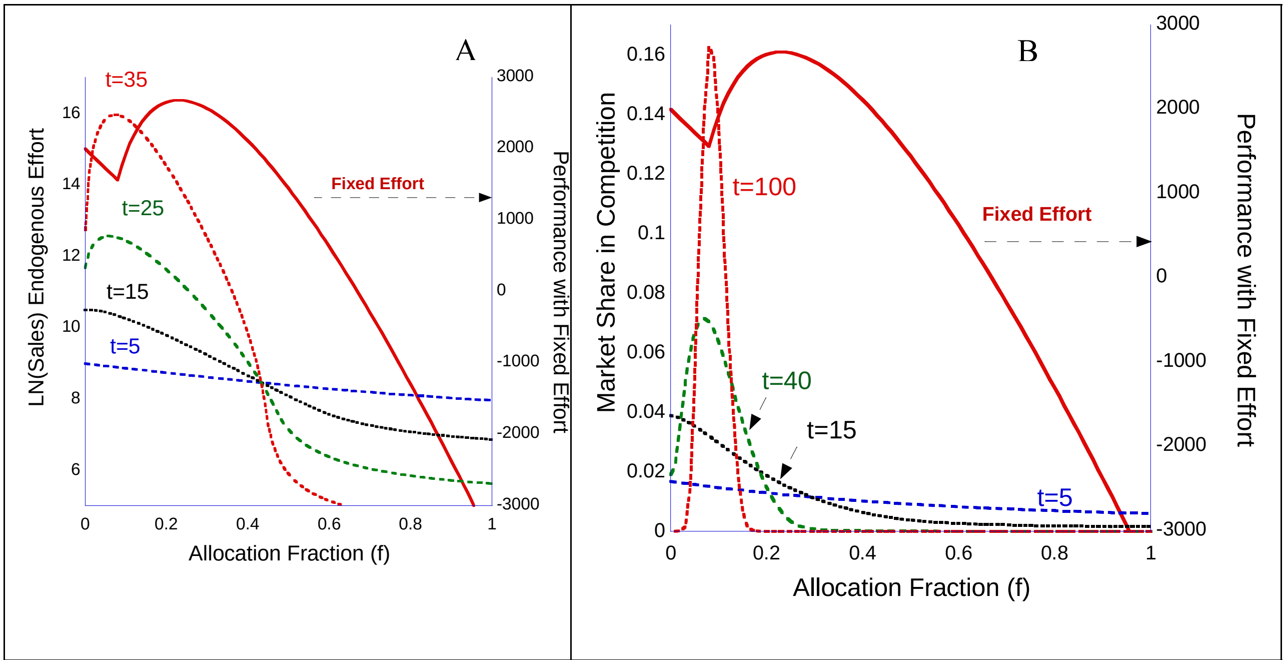


Figure S5– The result of analysis for the second alternative model, with dynamic capabilities impacting the productivity of operational ones. The overall behavior is very similar to the base case because the structure of delays involved between investment in each capability and its impact on the performance are very similar. Different resource allocation policies are compared at different times for both endogenous effort and competition cases. A) Results for the case with endogenous effort (left axis) is compared to existence of fixed effort levels to invest (right axis). Peak performance is at f=0.07 for endogenous effort, compared to 0.23 for fixed effort. B) The results for the case with 101 firms in uniform competition is compared to the fixed effort case. The firm with f=0.08 wins the competition. Furthermore, the strategic policy of f=0 dominates other policies if firms are picking their allocation policy rationally.

S7- Time compression diseconomies and organizational slack

Section 3-2 in the paper discusses the impact of time compression diseconomies on the dynamics of interest. Equation 13 specify the formulations used for this analysis and Table S1 provides the parameter values for the simulation experiments. Figure S6 describes the detailed results for the analyses under this condition.

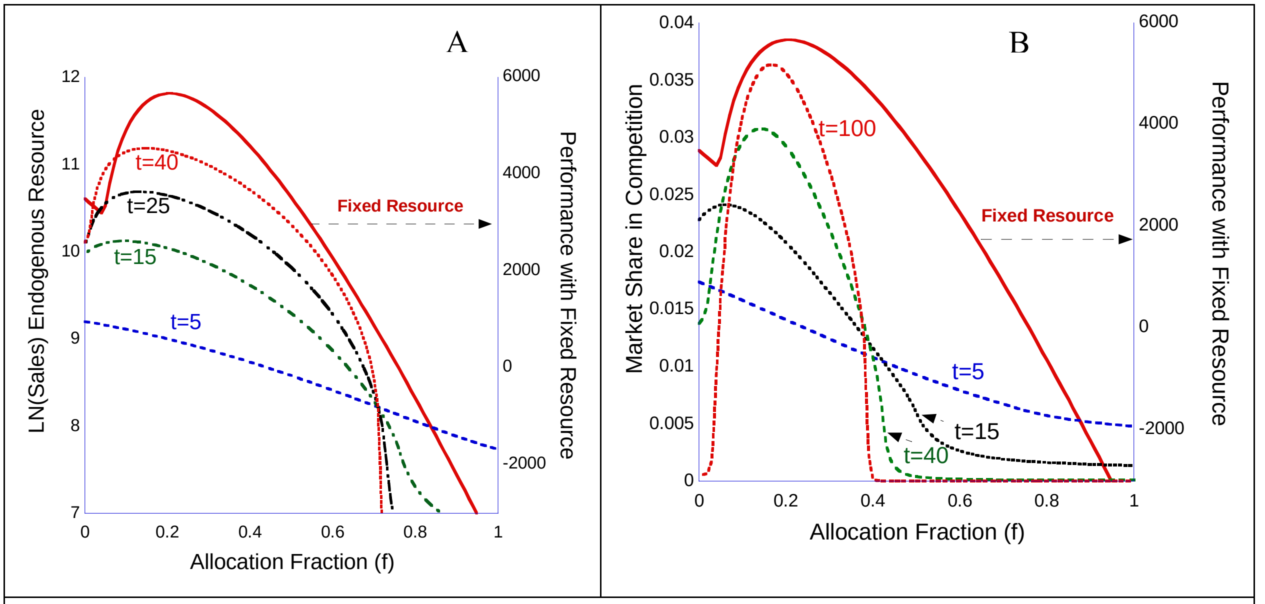


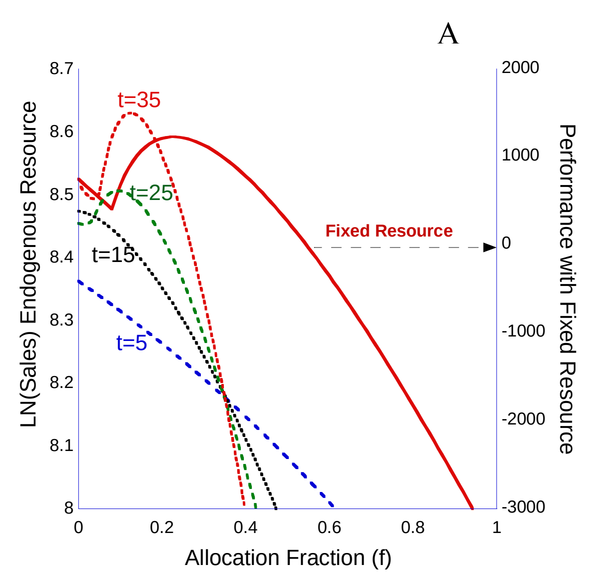
Figure S6– The result of analysis under time compression diseconomies. Faster investment in resources and capabilities lead to additional unit development cost. The resulting dynamics favor more balanced investment approaches and thus increase the relative value of long-term policies in presence of competition and growth opportunities. Different resource allocation policies are compared at different times for both endogenous effort and competition cases. A) Results for the case with endogenous effort (left axis) is compared to existence of fixed effort levels to invest (right axis). Peak performance is at f=0.15 for endogenous effort, compared to 0.21 for fixed effort. B) The results for the case with 101 firms competing with different levels of allocation fraction, f, is compared to the fixed effort case. The firm with f=0.17 wins the uniform competition. The game theoretic policy of f=0.10 dominates other policies in strategic competition.

Slack is captured by reformulating investment in the model as follows:

$$R = B.b \quad \text{(S13)}$$

$$\frac{dB}{dt} = (C_O.p - C_D.c_{CD} - c) - \frac{B}{T_B} \quad \text{(S14)}$$

Parameter values are reported in Table S1. Figure S7 reports the detailed results when including the slack in the firm investment process.



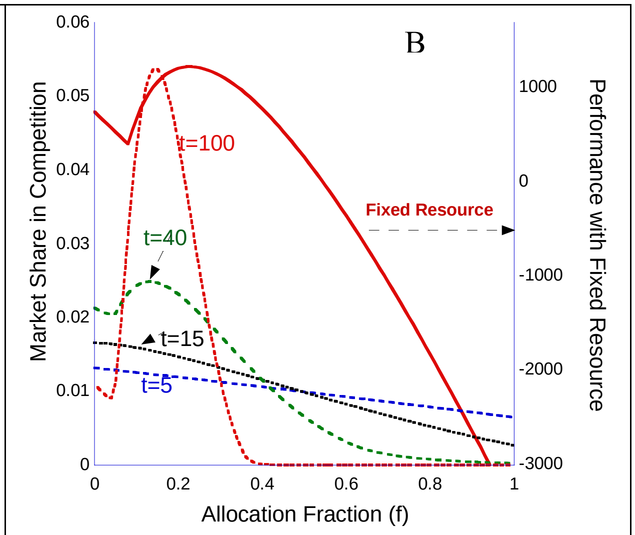


Figure S7– The result of analysis with 30 month of slack resources between performance and investment. The buffer in the reinforcing loop significantly slows down the growth opportunities and therefore ads to the value of long term capabilities. Different resource allocation policies are compared at different times for both endogenous effort and competition cases. A) Results for the case with endogenous effort (left axis) is compared to fixed effort case (right axis). Peak performance is at *f*=0.13 for endogenous effort, compared to 0.23 for fixed effort. B) The results for the case with 101 firms in uniform competition is compared to the fixed effort case. The firm with *f*=0.15 wins the uniform competition. The game theoretic policy of *f*=0.14 dominates other policies in strategic competition.

S8- Heterogeneous capability endowments and firm performance

We conducted additional analysis to find out how initial capability endowments impact the winning policy. The relationship between initial capability endowment and firm performance in a competitive market is a complex one. Not only firm's performance depends on its own initial endowments and allocation fraction (*f)* but also its performance depends on the initial endowments (and allocation policy) of other firms.

In our settings the initial operational capability is distributed Uniform(0, 60,000) and the initial dynamic capabilities are distributed as Uniform(30, 100) units. One may therefore consider capability endowments above average as relatively good. However, an initial endowment of 75 units for dynamic capability may or may not be large, depending on the random initial drawings for the other firms in the market: a few firms with larger initial endowments can significantly reduce the value of an initial endowment of 75 (or any other large value).

Moreover, the combination of the two capabilities and not any single one of them determines the initial capability standing. For example a firm may have a ranking of 5 among 100 firms in each capability endowment, but when looked at overall capability position, be the strongest in the market because each of the 4 companies with stronger initial standing in one capability lack competitiveness in the other. Furthermore, initial capability is not so important alone. There may be some firms with better capability endowments, but very poor allocation policies (typically very large *f* in our setting). Such firms, despite initially good standing, have no chance of success. In fact in our setting no firm is market leader after 100 months if they have $f>0.34$.

Another observation relates to the competitiveness of policies with high allocation fraction over the very long time horizons. One may expect that the impact of initial endowments would be washed away as time progresses, leading to the long-term dominance of the firm with the most efficient allocation policy in competition (e.g. 0.08 in this case). In fact the figure 5 of the paper may suggest a similar trend: as longer time horizons are considered, the tails of the distribution of the leading firms' allocation fraction shrink, suggesting that more of firms with high allocation fractions lose their leading position. While this observation is correct, the underlying dynamics are more subtle. Simulating the markets for very long time horizons (1000 months), we observe that some firms with high allocation policies (as high as $f=0.34$) continue to dominate the market after coming to power because of their rich initial resource endowments. The reason is that as these firms grow, their efficiency increases because of their increasing return to scale structure (in the base case). Therefore they can pass a threshold in size over which they become more efficient than small firms who are following the more efficient allocation strategy, and thus they lock into success in the market. However, these dynamics are possible only in markets with increasing return to scale. Over the long run markets with decreasing return to scale always shift to favor the firm with the most efficient allocation policy.

While it is hard to find the game theoretic efficient allocation policy in presence of heterogeneous resources, the same mechanisms are in effect for rational competitors. Firms that think they have a high initial resource endowment have the option of going with the strategy with higher long-term growth rather than focusing on fastest initial growth ($f=0$). Their initial capabilities can provide the engine of growth while they build their dynamic capabilities to the level that dominates the myopic competitors. Therefore we conjecture that efficient game theoretic solution depends on initial resource endowments and may be higher than the base case ($f=0$).

In summary, firms with superior initial capability endowments have a better chance of winning in the competition. In markets with increasing return to scale these firms can grow to more efficient sizes that compensate for their potentially poor allocation strategies. Moreover, the relationship between initial capability endowment and market performance is more compelling for firms who want to win with allocation policies that focus on the long-term. These firms can win only if their initial capability endowments are uniquely large in the market. Firms with lower capability endowments still have a chance at winning if their allocation policy is close to the efficient levels for the given market.

S9- Instructions for downloading and simulating the models

All the simulation models used in this study are available for independent analysis and inspection. These models are available as a .zip file attached to this submission.:

Once you unzip the file, seven simulation models (.mdl files) in Vensim ™ programming language are available, along with additional command files (.cmd), save lists (.lst) and sensitivity analysis control (.vsc) files. Vensim models can be easily opened, inspected, and simulated with the free Vensim Model Reader software available for download from:
http://vensim.com/freedownload.html

The following models are included in the package:

CapabilityDynamics_MultiFirm_Base.mdl: The model used in the base case analysis

CapabilityDynamics_MultiFirm_SatEfficiency.mdl: The model used for analysis with saturation of the efficiency of investment in operational capabilities (Section 3-1)

CapabilityDynamics_MultiFirm_DecRet.mdl: The model with decreasing returns to scale (Section 3-1)

CapabilityDynamics_MultiFirm_TimeCompDisecon.mdl: The model with time compression diseconomies included, discussed in section 3-2 of the paper.

CapabilityDynamics_MultiFirm_HetRes.mdl: The model with heterogeneous initial resource and capability endowments for the firms (Section 3-3).

CapabilityDynamics_MultiFirm_Alt1_CobbDouglas.mdl: The model with alternative, Cobb-Douglas firm formulation (Section 3-1).

CapabilityDynamics_MultiFirm_Alt2_Productivity.mdl: The model with the second alternative formulation putting the impact of dynamic capability on the productivity of operational capability (Section 3-1).

CapabilityDynamics_MultiFirm_Buffer.mdl: The model with the slack resources (Section 3-2)

You can open each model and analyze it using the user friendly simulation environment provided by Vensim. Variable names are largely consistent with the notation in the paper, with some additional variables included in the model to facilitate the analysis process.

You can view the equation for each variable by selecting that variable and clicking the “Doc” button in the left toolbar. You can follow the procedure below for simulating and analyzing the model behavior:

- First choose a name for your simulation and enter it in the field for simulation name in the middle of the top toolbar: 

- Click on the SET button to the left of this name.
- Now change the parameters of the model as desired. The best place to do so is to go to the “control panel” view (Press Page Down until you arrive at the second view) where you can change all the main parameters. The current values of the parameters are shown if you click on each parameter.
- Simulate the model by clicking the Run button in the top toolbar: .

Examining the behavior:

- You can also use the tools in the left toolbar to see the behavior of different variables. Select a variable by clicking on it and then click on the desired tool. A graph or table of the variable of interest will be shown.

However, you can not edit the model in the Vensim Model Reader. For that purpose you will need the professional or DSS versions of the Vensim. The other files included in the .zip file are useful for replicating the analysis in the base case using the command scripts provided. These files will significantly simplify the replication of the results and additional analysis. A DSS or Professional version of Vensim is required for using these capabilities.