If Higher Pay Is Profitable, Why Is It So Rare? Modeling Competing Strategies in Mass Market Services

Citation: Rahmandad, Hazhir and Zeynep Ton. "If Higher Pay Is Profitable, Why Is It So Rare? Modeling Competing Strategies in Mass Market Services." Organization Science 31, 5 (February 2020): 1053-1312 © 2020 INFORMS

As Published: http://dx.doi.org/10.1287/ORSC.2019.1347

Publisher: Institute for Operations Research and the Management Sciences (INFORMS)

Persistent URL: https://hdl.handle.net/1721.1/130419

Version: Original manuscript: author's manuscript prior to formal peer review

If higher pay is profitable, why is it so rare?
Modeling competing strategies in mass market services

Hazhir Rahmandad, MIT
hazhir@mit.edu

Zeynep Ton, MIT
zton@mit.edu

ABSTRACT

Several case studies suggest that firms targeting mass-market services can align profitability with jobs offering a living wage, stable schedules, and engaging work. Yet few do. To understand this puzzle, we draw on theories of firms as systems of interdependent choices. Building on a few cases, we map the processes connecting managerial choice to performance and formalize the resulting performance landscape. In a strategy space defined by two dimensions—task richness and compensation—two local profitability peaks emerge: one with low compensation and low task richness and one with high compensation and high task richness. The bimodal landscape results from complementarity among choices and is robust when the strategy space is expanded from two to six dimensions and under many alternative parameterizations. Exploring how firms discover, move to, and remain at the high-compensation–high-task-richness peak, we find three challenges to this strategy: (a) *contextuality*—adoption, imitation, and replication is harder for strategies that rely on interdependences among components and thus require significant customization for each context; (b) *temporal complexity*—strategies depending on long-term and synergistic investments and slow-moving reinforcing feedbacks are hard to learn, due to misleading performance feedback; and (c) *variable demand with no inventory buffers*—efforts to adjust labor supply to highly variable demand in services often lead to unstable schedules given with short notice that drive quality employees away and compromises the strategy. These mechanisms can undermine promising strategies even if the actual performance landscape includes a small number of local peaks.

Acknowledgments

We are thankful to Matt Amengual, Emilio Castilla, Greg Distelhorst, Felipe Csaszar, Allen Graham, Michael Jacobides, Sarah Kalloch, David Keith, Erin Kelly, Tom Kochan, Rogelio Oliva, Paul Osterman, John Sterman, and Ezra Zuckerman for their valuable conversations and suggestions. We also are grateful for the comments of seminar participants at MIT, Stanford and London Business School and reviewers and conference attendees at AOM, CSOL, INFORMS, ISDC, SMS, Strategy Science, and TOM.

INTRODUCTION

From behavioral theories of management (McGregor 1960) to studies of human resource practices (Kochan and Osterman 1994) in manufacturing (Ichniowski et al. 1997), call centers (Batt 1999), airlines (Bamber et al. 2009), express delivery (Ling et al. 2009), and health services (Mayfield 2010), management scholars have shown that different labor strategies can coexist in a market. Some companies choose to invest heavily in their employees and maximize employee involvement (e.g., paying them more than industry average and providing an engaging work environment) while others do not prioritize employee involvement. When the heterogeneity in strategies is not explained by distinct positioning choices (Porter 1996), why are employee involvement strategies so rare? That's the question we seek to answer in the context of mass market services in the United States. In answering that question, we contribute to theories of firms as interdependent choices and the adoption and maintenance of heterogeneous strategies more broadly.

Mass market services—including retail, leisure, and healthcare and social services—account for over 30% of US employment (when including retail, leisure, and healthcare and social services. Bureau of Labor Statistics 2017a). Most firms in these industries minimize labor costs with (a) low wages—median hourly wages are $9–12 (Bureau of Labor Statistics 2017b), (b) poor benefits (Carre et al. 2010), (c) routinized low-skill tasks (Appelbaum and Schmitt 2009), and (d) unstable scheduling based on short-term demand predictions with the possibility of last-minute adjustments (Lambert 2008). We call this strategy bundle *Cost Minimization* (CMin).

However, case studies in companies such as QuikTrip (a US chain of over 750 convenience stores), Costco (a warehouse club with over $126 billion in sales), Mercadona (Spain's largest supermarket chain), and Trader Joe's (a US supermarket chain) suggest that an employee involvement strategy can be not only profitable but even profit-maximizing in mass market services (Ager and Roberto 2013; Ton 2014; Ton and Harrow 2010). Compared to their competitors, these companies offer higher wages (e.g., average hourly wages at U.S. Costco warehouses were slightly over $23 in 2019), more predictable schedules (e.g., Mercadona provides work schedules a month in advance), and substantial growth opportunities (e.g., all store managers at QuikTrip are promoted from within). In return, they not only have benefited from turnover rates as low as 10% of the industry average but also have regularly outperformed industry benchmarks in productivity, customer satisfaction, and—in some cases—

profitability. These studies highlight an alternative strategy bundle consisting of (a) operational choices that increase frontline employees' productivity, contribution, and involvement in continuous improvement and (b) short- and long-term investment in employee skills and motivation such as more training, higher wages, and stable work schedules. We call this strategy bundle *Involvement Maximization* (IMax).

If the IMax strategy can be profitable for firms targeting a mass market, why do most choose the CMin strategy (Appelbaum and Schmitt 2009; Carre et al. 2010)? Building on theories of firms as systems of interdependent choices (Fleming 2001; Levinthal 1997; Siggelkow 2011), we address this question in two steps. First, using case study data, we follow the pioneering work of Siggelkow (Siggelkow 2001, 2002a) by mapping the interaction patterns among service firms' strategy components. We then use system dynamics (Sterman 2000; Torres 2019) to quantitatively model the mapping from strategies to expected performance (i.e., the performance landscape) for a price-taking firm in a competitive mass market.

We find a bimodal landscape, with two local peaks with comparable heights and basins of attraction. These local peaks correspond to IMax and CMin, providing an explanation for the observed strategy variation that is distinct from strategy variation—such as cost leadership versus differentiation—attributable to positioning (Porter 1996). Our empirically motivated model corroborates the theoretical explanations of firm heterogeneity based on ruggedness of performance landscapes (Levinthal 1997). However, contrary to more abstract NK models, we do not find evidence for a plethora of local peaks or for a small basin of attraction for IMax that could deter firms from adopting this strategy. Instead, we put forward three new explanations for its low adoption.

First, IMax suffers from what we call contextuality (Porter and Siggelkow 2008), as it requires getting several things right for the context at hand. Consider two locally dominant strategies (local peaks) with comparable performance, only one of which (IMax) includes reinforcing feedbacks that make it sensitive to market specifics. IMax would then be less valuable as an imitation target and would require customization by each new adoptee, reducing its overall frequency. Second, firms adapt through feedback on the outcomes of exploratory moves. Prior models have largely assumed unbiased feedback on the outcomes of exploratory moves. However, short- and long-term impacts of such explorations often differ, creating temporal complexity in adaptation. For example, boosting compensation to attract and retain higher-quality employees leads to a worse-before-better dynamic, where the longer-term benefits depend on synergies present in IMax but not in CMin. Those synergies accumulate slowly and may not be fully accounted for in managerial calculus. Third, given lack of inventory buffers in services, companies often respond to highly variable demand by adjusting their labor supply to customer traffic in short increments. This causes unstable schedules, which then hurt strategies that depend on quality employees. However, investments in organizational capabilities could be used as a buffer in the face of demand variability, reducing the need for unstable schedules and restoring IMax.

Beyond refining our understanding of competing strategies in mass market services, these results inform the theory of firms as interdependent choices and our broader understanding of the adoption and maintenance of heterogeneous strategies. In the next section we position our work within this literature before discussing our methods, model, and results.

Theoretical views on the coexistence of strategies

To understand differences in organizational strategies, it is conceptually helpful to distinguish heterogeneity due to market positioning from heterogeneity among firms targeting the same market segment (Adner et al. 2014; Siggelkow 2001). Our focus is on the latter. There are two competing theoretical views on strategies targeting the same segment. The classical view, rooted in the economics literature, holds that a firm's performance landscape—the mapping from its managerial choices to its performance—is often convex with a single peak (Mas-Colell et al. 1995). Finding the best strategy for maximizing profits is thus feasible—even easy. Therefore any heterogeneity in strategies should be attributed to firms targeting different market segments, or delays inherent in firms' identifying and transitioning to the optimal strategy. The alternative view, recognizing interdependence among organizational choices (Fleming 2001; Levinthal 1997; Siggelkow 2011), has formalized rugged performance landscapes (NK models), with many locally dominant strategies[1] (Levinthal 1997). Because the global best strategy is then hard to find, adopt, or imitate (Rivkin 2000, 2001), local adaptation guides the evolution of organizational strategies, leading firms to settle on multiple local peaks.

While models of firms as interdependent choices often do not explicitly separate positioning from performance within a market segment (for an exception, see (Adner et al. 2014)), their account of heterogeneity is independent of positioning and applies to firms targeting the same segment. They also

[1] In this paper we use the term "strategy" to refer the bundles of choices specifying a firm. Other terms, such as 'configuration' and 'design' are also used in the literature to refer to those bundles.

explain the relative frequency of each strategy based on the size of its basin of attraction—the region of strategy space from which local adaptation leads to that particular peak.

The large gap between the two views has persisted as theorists have assumed concave or rugged landscapes and explored the implications of optimal choice or local adaptation in these hypothesized topologies. Modeling performance landscapes based on actual interactions among organizational choices can bridge these views, but progress on this front has been limited (Baumann et al. 2019; Porter and Siggelkow 2008). There are a few rich descriptions of such interactions (Siggelkow 2001, 2002a) and the resulting challenges in adopting different strategies—for example, in the auto industry (Pil and MacDuffie 1996)—but none have been quantified. So it is not known if, in practice, it is ruggedness that explains divergent strategies targeting the same segment and whether other explanations are relevant. We tackle these open questions by grounding quantitative models of strategy adoption in the context of mass market services, a promising setting for a few reasons. First, the gap between IMax and CMin is large and hard to explain away based on unobserved heterogeneities among firms targeting the same market. Second, investments in service capabilities and employee quality, common in this sector, are at the heart of the tradeoffs managers face in adopting strategies in a wide range of settings and can therefore reveal dynamics of more general interest. Finally, a deeper understanding of competing strategies in this large and growing sector is of broad practical interest even beyond its contributions to organization theory.

METHODS

We seek to (1) identify various interactions among strategic choices in mass market services, (2) quantitatively model the resulting performance landscape, and (3) investigate the factors influencing the adoption of alternative strategies. We follow a tradition of constructing simulation models grounded in case study data to formalize qualitative theories of the phenomenon under investigation (e.g., Repenning 2002; Sastry 1997). Case studies (a) allow us to identify relevant relationships and set plausible ranges for various effects, (b) offer concrete examples to enhance external validity, and (c) identify the boundary conditions for the formal model. Using the model, we quantify different strategies (e.g., IMax and CMin), trace the dynamics resulting from strategic change, and assess the contingency of results on various factors. We intend our model to reflect regularities that apply beyond the (mostly) retail context of our cases. Nevertheless, lacking quantitative estimation and comprehensive coverage of all mass market services, our approach remains limited in generalizability and should be seen as theory building rather than testing. Moreover, reporting results from two methods in a limited space, we are bound to make tradeoffs in the depth of our treatment. Here, we opt for a shorter presentation of the qualitative data and cases to accommodate the simulation model and its results.

Our case studies were conducted over a span of 19 years; the overarching goal was to understand retail store operations in detail. We observed CMin strategy at Borders Group, The Home Depot, and Metro and IMax strategy at Mercadona and QuikTrip. Mud Bay, a chain of pet stores in the Northwest transitioned from CMin to IMax, as did Quest Diagnostics in its call centers. A few retailers—The Container Store, Zara, and Market Basket—displayed certain aspects of the IMax strategy. Data collection across cases was not uniform, but commonly included extended visits, interviews with stakeholders at different levels, and archival data. Through these cases, we identified the processes by which various organizational features jointly create value for customers, employees, and shareholders. We also interviewed employees at different levels (from executives to frontline workers) at Costco, another IMax retailer; Walmart, which is interested in transitioning from CMin to IMax; and several CMin retailers. Details on these companies are reported elsewhere (Ton 2014; 2017) and references therein); here, we offer relevant examples to motivate the model and discuss our findings.

Our purpose required trading off the elegance of a stylized model focused on a single theoretical mechanism against capturing the richness of interactions revealed from case data and relevant for understanding the empirical context. Our model captures managerial choices and interactions required for building a realistic performance landscape, uses intuitive constructs that ground the model in the relevant region of parameter space, and captures transition dynamics we found critical to understanding the adoption of various strategies. Nevertheless, we make no claim of completeness. Given our case data, we focus on specific human resource and operations choices and exclude factors such as labor supply constraints, marketing strategy, and outsourcing. To avoid conflating our arguments with positioning considerations, we focus on price-taking firms, assume homogeneous customers, and exclude quality differences or cumulative historical advantages (e.g., due to past performance).

We followed a layered model-validation approach (Forrester and Senge 1980; Homer 2019). Face validity and robustness in extremes was tested for each formulation in isolation. System-level robustness to extreme inputs, such as sudden removal of employees, was examined in another set of tests. Given the generic model, calibration to a single case was not pursued, but we tested for qualitative correspondence of the model outputs with empirically observed trajectories. The model being generic, reported numerical results are only illustrative and should not be interpreted as empirically reliable.

A SIMPLE MODEL OF SERVICE OPERATIONS

Our model should simulate a service firm's performance for different combinations of managerial choices by formalizing interdependences among those choices. In contrast to prior theoretical models, we do not start with a given set of choice interdependences; rather, we let those interdependences emerge from observable lower-level interactions among operational processes. This approach is informed by system dynamics' focus on building models of organizational dynamics grounded in observed operations. Below we document those operations and their interactions, formalize them into model equations, and specify their linkages to managerial choice, which generates the realized interdependences among those choices. We develop and analyze our model in two steps. First, we build a simple model that captures the more salient features of service operations. This model informs intuitions about the shape of the performance landscape. We then introduce the more complex mechanisms moderating the adoption and effectiveness of IMax and CMin. Those additions inform broader challenges to adoption of IMax that inform our theoretical contributions. Online appendices A1 and A2 supply complete model documentation (Rahmandad and Sterman 2012).

In the following sections, it helps to imagine a retail operation, such as a supermarket, although most of the mechanisms apply more broadly to services. Retailers manage merchandise (e.g., forecasting, ordering, and logistics—often planned centrally), customer service (e.g., checkout, cleanliness, and interaction), and employees (e.g., staffing, compensation, hiring, and training). They use capital such as cash registers, coolers, and systems for merchandise planning, staffing, and scheduling. Some of this capital have similar costs and returns across firms, while others are integrated into more complex organizational processes with heterogeneous performance. As in most service operations, there is a lot of variation due to customers—when they come, what they want, and how they evaluate the service. Some supermarkets give a lot of discretion to store employees (e.g., in ordering inventory, helping customers, and process improvement) and cross-train them, while others have employees perform only simple, standardized tasks (e.g., checkout or shelving).

Service capacity. Service capacity—the number of customers that could be served per unit of time--depends on various types of resources that managers control, such as organizational routines and human resources. Capacity determinants also depend on the nature of tasks. Different types of tasks vary significantly in their cognitive and emotional demands. Some are routine and low-skill, while others require degrees of choice, discretion, and cognitive processing ranging from a Home Depot employee helping you find the right putty to a supermarket employee determining how many pounds of organic gala apples to order to replenish inventory. The number of employees engaged in the first category offers a good indication of their combined contribution to output, but for the second, individual knowledge, skills, and abilities (i.e., human capital) as well as motivation should be considered explicitly (Ployhart and Moliterno 2011). For simplicity, we combine employees' human capital and motivation dimensions into the "employee quality" (Q) construct, and use the term quality exclusively for this construct.

A parallel distinction exists between different types of capital. Some—for example, a cash register—are available to all firms with similar costs and returns regardless of employee quality; we call those "assets" (A). Others are productive only when embedded in more complex organizational routines and their costs and performances are tied closely to how well they are customized, operated, maintained, and improved. For example, the processes for ordering merchandise, shelving, customer interaction, and store upkeep all benefit from customization and employee engagement. Following the resource-based tradition, we call the capital embedded in more complex organizational routines (service) *capabilities* (C). For clarity, we use the term *capability* only in reference to the organizational construct, using the term *quality* in reference to individuals' skills, abilities, and motivations.

The distinctions between rich and routine tasks and between capabilities and assets allow us to distinguish two dimensions of service operations: how much service capacity depends on labor (vs. capital) and how much capacity benefits from employee quality. We use a modified Cobb-Douglas production function to quantify service capacity (P) as a function of these four factors:

$$P = \kappa C^{\alpha\beta} A^{\alpha(1-\beta)} {E_S}^{(1-\alpha)} Q^{(1-\alpha)\beta}, \tag{1}$$

where E_S is the number of employees allocated to serving customers, α is the contribution of capital relative to labor, β is the richness of tasks, and κ is a normalizing constant (variables that change over time are upper-case and constants are lower-case or Greek letters). This leads to a traditional Cobb-Douglas function ($P = \kappa A^{\alpha} E^{(1-\alpha)}$) if task richness is assumed to be 0 (i.e., all capital is assets and employee quality has no impact on capacity). On the other hand, a service operation which only relies on labor would have another simple capacity function, $P = \kappa \mathrm{E} Q^{\beta}$ (Equation 1b), which we use in our simple model. (Note that in the absence of capabilities, all labor directly contributes to capacity; that is, $E_S = E$.) More generally, task richness has two distinct but related roles: it regulates the balance between assets and capabilities and it moderates the contribution of employee quality to productivity.

Within a range of feasible options, task richness (β) is an organization-design choice (Brusoni and Prencipe 2006; Sinha and Van de Ven 2005). Managers can reduce β by simplifying tasks, assigning each employee to a single task, reducing frontline employees' role in shaping routines, and reducing the required cognitive skills. They can increase β by relying on more complex routines, bottom-up process improvement, job rotation, employee empowerment, and more direct interaction with customers. For example, Mercadona views all service operations as processes subject to Total Quality Management (TQM) principles of continuous process improvement by engaged employees. The richness of even so routine a job as checkout can be increased by enabling employees to identify pricing errors, offer opinions on products, solve customers' problems, accept returns, and customize packing.

Employees and their quality. The number of employees (E) and their quality (Q) affect service capacity. The stock of employees adjusts towards the level indicated by current demand (D), with an adjustment time constant, μ, which represents a potential managerial choice: how quickly management attempts to match labor hours to demand through changing schedules and using part-time labor. Various factors may affect employee quality, among which the most salient are compensation and benefits (Milkovich et al. 2014). For example, to recruit and sustain a high-quality workforce, QuikTrip, Mercadona, and Costco all offer wages significantly more than the industry average and generous benefits (e.g., Mercadona offers maternity and day-care benefits). We use $(\frac{c}{c_N})^{\theta_c}$ to quantify the effect of compensation, c (normalized by industry norm, c_N), on employee quality (Eq. 2). θ_c may vary by employee type (e.g., nonprofits' labor pool may be less compensation-sensitive than that of financial services) and tightness of labor market. In this section, we leave out the other contributors to employee quality and its dynamics:

$$Q = \left(\frac{c}{c_N}\right)^{\theta_c}. \tag{2}$$

Demand, revenue, and profits. The number of customers served (L) is bounded by capacity (P) and demand (D) (Eq. 3). We start in this section with constant demand (Eq. 4). Net revenue from sales (R) is customers served multiplied by the average profit margin per customer (M) (Eq. 5). Consistent with the literature (Chen and Sandino 2012; Chuang and Oliva 2015; Raman et al. 2001), we observed that high-quality employees affect margin by reducing waste, spoilage, and shrink; by improving record-keeping;

by offering feedback on packaging and product features that cut manufacturing, logistics, and shelving costs; and by more effectively surfacing and addressing customer needs and thus increasing sales per customer. For example, Mercadona annually saves over €9.5 million through employee-driven improvements, including changes to the packaging of eggs, water, milk, coffee, and rice. These effects change margin per customer (M) around its base value (m_b) with elasticity δ_Q (Eq. 6). Finally, to calculate profits (π), we subtract from net revenue the costs of employees and fixed costs (Eq. 7).

$$L = Min(P, D) \tag{3}$$

$$D = d_b \tag{4}$$

$$R = LM \tag{5}$$

$$M = m_b Q^{\delta_Q} \tag{6}$$

$$\pi = R - cE - c_{Fixed} \tag{7}$$

Emergence of a bimodal performance landscape

Replacing terms in Equation 7 with terms from Equations 1–6 and matching capacity to demand, equilibrium profits, π_{eq} (i.e., excluding employee adjustment lags impacted by μ), can be expressed as a function of the two managerial choices, c and β:

$$\pi_{Eq} = d_b \left(m_b \left(\frac{c}{c_N}\right)^{\theta_c \delta_Q} - \mathrm{c}\frac{1}{\kappa\left(\frac{c}{c_N}\right)^{\theta_c \beta}} \right) - c_{Fixed} \ . \tag{8}$$

Equation 8 summarizes a simple performance landscape based on the lower-level operational interactions we observed. Given the one-to-one association between compensation and employee quality (Eq. 2), it is simpler to express the performance landscape in terms of quality, Q:

$$\pi_{Eq} = d_b \left(m_b Q^{\delta_Q} - c_N Q^{\frac{1}{\theta_c}} \frac{1}{\kappa Q^{\beta}} \right) - c_{Fixed} \ . \tag{8b}$$

In Equation 8b, the first term in parentheses ($m_b Q^{\delta_Q}$) is profit margin per customer and the second is the cost of employees per customer, consisting of per-employee compensation ($c_N Q^{\frac{1}{\theta_c}}$) with the $\frac{1}{\kappa Q^{\beta}}$ term converting per-employee cost to per-customer cost. In this function, task richness and employee quality are complements (i.e., $\frac{\partial^2 \pi_{Eq}}{\partial \mathrm{Q}\, \partial \beta} > 0$; see Appendix A3 for analytical proof). With low employee quality ($c<c_N$ or Q<1), additional task richness has limited benefits and is costly because it increases mistakes (thus eroding margin) and requires more employees (because task richness ties labor needs to employee quality). As a result, increasing task richness is a bad idea, creating a local peak at $Q<1$ and minimum task richness ($\beta=0$). This local peak resembles the CMin strategy: it minimizes task richness and pays employees the minimum wage. However, the complementarity (i.e., $\frac{\partial \pi_{Eq}}{\partial \beta}$ increasing with Q) means that task richness becomes more attractive at higher Q. In fact, at higher employee quality levels ($c>c_N$ or

Q>1), an increase in task richness or employee quality can increase profits: employee quality improves margins (the $Q^{\frac{1}{\theta_C}}$ term), and both quality and task richness reduces the number of employees needed per customer ($\frac{1}{\kappa Q^{\beta}}$ term). If for some values of Q and β these benefits exceed the compensation costs of higher-quality employees ($Q^{\frac{1}{\theta_C}}$), increasing both choices would enhance profits. Thus, with strong enough complementarity, a second local peak is generated at maximum β (=1) and a high value of employee quality/compensation; this peak resembles the IMax strategy. In short, two peaks emerge because complementarity between task richness and employee quality changes the calculus on task richness depending on employee quality (and vice versa). Medium levels of task richness are thus inefficient: If we have good (Q>1) employees, we want to increase task richness to make full use of their quality. Otherwise, we want to minimize task richness to avoid the costs of poor employees (Appendix A3 offers analytical bounds on bimodality). The basic argument here also (a) applies to smaller ranges of β, (b) works in a general class of operations for which task richness complements employee quality, and (c) leads to a bimodal landscape even with modest complementarity in the baseline parameters (m_b=\$4/customer; θ_C=0.7; δ_Q=0.1; κ=4000; c_N=\$2000/month). A bimodal landscape offers an explanation for the coexistence of distinct strategies. Yet this model excludes factors that may change the strategic calculations and thus its numerical outputs are not robust (e.g., the IMax peak entails unrealistically high compensation). Moreover, by focusing only on equilibrium results of rapid interactions among variables (e.g., the impact of compensation on employee quality is fast), this model ignores the dynamics relevant to adopting different strategies. We therefore go on to refine this account.

A MORE REALISTIC MODEL OF SERVICE OPERATIONS

Our simple model focused on direct, i.e. one-way and rapid, effects of variables on each other. Based on our cases, we introduce additional determinants of employee quality and two new constructs—accumulations and feedback loops—that help us analyze why some strategies are more likely to be adopted than others. Accumulations, such as building service capabilities or a quality workforce, introduce delays between managerial choices (e.g., higher compensation) and outcomes (e.g., higher employee quality). Feedback effects emerge from endogenous interactions among system variables. Feedback can create slower dynamics absent exogenous interventions, often making its effects under-appreciated in day-to-day practice. Here we use direct, cumulative, and feedback effects to organize a qualitative discussion of new model components (for complete equations, see Appendices A1 and A2).

Figure 1 summarizes those mechanisms visually. In that figure accumulations are highlighted as stock variables (shown in rectangles) and feedback loops are named and labeled using circular arrows.

<Insert figure 1 around here>

Additional direct determinants of employee quality. Job attractiveness—and thus employee quality—depend on factors beyond compensation. Employees desire predictability, consistency, and control over their working hours (Henly and Lambert 2014). However, demand in the service sector is often noisy, which we capture with a random noise term, *N*, in the demand function. When management rapidly adjusts workforce levels to noisy customer demand, the instability makes for unattractive jobs. One worker at a CMin retailer told us, "My life is always in a turmoil. Every day. ….. You need a set schedule to be able to sleep. ….. As far as trying to have a life and doing things with people, you can't." We use the employee adjustment time (μ) as a proxy for scheduling practices: lower μ reduces job attractiveness when demand variability (*N*) is notable. On the other hand, feedback, autonomy, and meaningfulness are among the drivers of intrinsic motivation (Hackman and Oldham 1975). We therefore include a proxy—task richness—as a direct determinant of job attractiveness. Finally, employee quality (*Q*) is directly affected not only by job attractiveness but also by the initial screening and training of recruits.

Accumulations: Service capabilities and employee quality. Both service capability and employee quality are inertial concepts—stocks—that change slowly through cumulative processes. It takes months for an increase in a direct determinant of employee quality, such as compensation, to enhance the average quality of the workforce through the hiring of better employees and turnover of the current pool. Likewise, organizational service capabilities consist of inertial processes and routines built only through long-term investment and subject to erosion through turnover, obsolescence, and random deviations. For example, QuikTrip had over time built a few distinguishing processes, including (a) standards allowing no more than three customers per cashier line and no more than a one-minute wait, (b) a daily activity worksheet that ensured store upkeep and improved staffing, and (c) a sophisticated mystery shopper program tied to significant bonuses. Capability investments are manifested in employees solving problems, coordinating and collaborating, and improving existing processes. For example, the implementation of RFID (radio frequency identification) technology in the German retail chain Metro required the close collaboration of management, suppliers, store employees, and IT staff. It took several months of training, process improvement, and system adjustments before a reliable system was in place.

Capability building depends on employees: quality employees engage in change initiatives, notice opportunities for improvement, and can pick up new skills and processes (Hatch and Mowery 1998). For example, Zara stores are empowered to track customer demand trends and feed that information to headquarters staff who work with the designers, bringing new customized designs to a store in as little as three weeks. However, customization of product offerings to local trends is only valuable when employees are motivated and capable; otherwise, such flexibility could cause coordination challenges and subpar product designs. Mercadona's effectiveness in using TQM is dependent on its ability to attract and retain capable and motivated employees. High-quality and experienced employees (a) get to know customers by name and provide recommendations to them, (b) use the resulting knowledge to optimize the product selection both locally and nationally, and (c) spearhead improvements in the use of barcodes, supply chain automation, store ambience, and store flow. Moreover, quality employees often actively preserve service capabilities, introduce fewer errors, and foresee and prevent disruptions. For example, at Mercadona and QuikTrip, employees avoided costly stockouts by following replenishment and ordering procedures and kept stores clean and orderly. Job attractiveness also affects organizational capabilities through turnover, which brings loss of knowledge and social capital and can disrupt routines (Dess and Shaw 2001), thus speeding up capability erosion. At the former bookstore chain, Borders, stores with high employee turnover also had more operational problems.

Feedback effects: Rewarding environment, preservation of knowledge, and learning. The dynamics of employee quality are also subject to a few feedback effects. First, on-the-job learning enhances employee quality endogenously. Because there are decreasing returns to experience, the resulting feedback loop is balancing (*B1: Learning*); that is, increased employee quality slows down further increases. Because employee quality cannot be enhanced indefinitely by any combination of its determinants, we bound Q by a maximum value. There are also two reinforcing loops that regulate the long-term trajectory of employee quality. First, better employees can be recruited and retained when the work environment already includes motivated and knowledgeable colleagues who enhance teamwork and trust (Cable and Turban 2003). For example, The Container Store encourages employees to help each other by filling in when one has a personal emergency. A QuikTrip employee noted: "QuikTrip is more than just a convenience store… It's a family… You do what you love and you make customers happy. That's what [is] most important here." On the other hand, low-quality employees may receive a signal of mismatch in high-quality environments and leave. A QuikTrip manager elaborates: “The pace of work is too hard for some people and they exit quick. And the morale of the team really runs them off. I mean the peer pressure.” In Figure 1, the link from *Employee Quality* to *Job Attractiveness* captures the impact of work environment and completes the *R1-Rewarding Environment* loop which can endogenously enhance the workforce. On the other hand, job attractiveness also influences voluntary turnover, creating a reinforcing loop (*R2-Preserving Knowledge*) when quality employees are retained. For example, annual turnover for full-time employees is about 13% at QuikTrip and can go as low as 3.8% at Mercadona, compared to over 100% for the industry.

Profits and managerial choices. In the detailed model, we include additional terms (compared to Eq. 7) in the profit equation to capture costs of capital (capability-building and assets), hiring, and training. The resulting model includes seven managerial decisions: (1) task richness, (2) compensation, (3) employee adjustment time, (4) staffing levels, (5) assets, (6) recruitment and training costs per person, and (7) fraction of labor allocated to operational and customer service tasks (vs. capability building). Since analyzing a high-dimensional strategy space is complex, we focus the analysis on the more strategic choices and formulate the rest as decision rules contingent on the first set. We later assess the robustness of those results to treating all decisions as strategic choices. The two strategic levers we select are task richness and compensation. Task richness (β) is a business-design choice that informs (a) the balance of capabilities and assets, (b) the role of employee quality in performance, and (c) the quality of jobs from the employee’s perspective. Compensation (c) plays an important role in employee quality and costs. In one analysis, we turn on demand uncertainty (N) and include employee adjustment time (μ) as a third strategic choice to assess the impact of unstable schedules (μ is inconsequential when demand is stable). Given a choice of task richness and compensation, we assume that managers are very good at making the other four decisions (items 4–7 above). We adopt this strong assumption because it offers a clear benchmark for formulating various decisions. We note that this assumption may downplay the relative benefits of IMax, since our cases revealed worse management and more operational inefficiencies among firms following CMin than among those following IMax.

Parameterization. Our data suggest the existence and range of effects but do not provide point estimates for a given relationship’s strength. Therefore, in our model parameterization (see Appendix A2 for parameter values), we follow three guidelines. First, the model is quantified to roughly reflect the operations of a medium-size low-cost retail store. Second, we choose conservative elasticity values, mostly in the 0.1 to 0.2 range (i.e., a 7%–15% increase in the response variable as a result of doubling the explanatory variable). Finally, we chose small returns on hiring and training, which keeps these costs low in our model and further contributes to a conservative model set-up (that is, it favors CMin, which faces large turnover rates). We use detailed sensitivity analysis to assess the impact of parametric assumptions.

ANALYSIS OF THE DETAILED MODEL

In this section, we assess the robustness of the bimodal landscape that emerged in the simple model, then use three sets of analyses to inform factors impacting the adoption of a particular strategy. Specifically, we (a) show how different strategies may vary in their contextuality, which impacts their attractiveness, (b) examine the disequilibrium dynamics of moving on the landscape and how those dynamics can mislead managers and underpin the temporal complexity of adaptation, and (c) show how demand variability can induce unstable schedules and compromise IMax, but capability buffers can reclaim the strategy. (Online Appendices S5 and S6 provide more in-depth analyses of the model, the impact of feedback loops, and model parameters.)

Persistence of a bimodal performance landscape. Using the detailed model, we vary compensation and task richness within a wide range and track the equilibrium profits on the resulting strategy space to formalize the performance landscape. This exercise is similar to the closed-form solution (Eq. 8) in the simpler model and its results are reported in Figure 2 as a contour map. The two local profit peaks persist with our base case parameters. One optimum is at low compensation ($1000/month) and a task richness of 0, offering a monthly profit of $47,000, while the other has higher compensation ($4200/month) and a task richness of 1 with profitability of $49,000/month. These peaks continue to correspond qualitatively to the CMin and IMax strategies we observed (optimum IMax compensation is somewhat higher than our observations due to the constant elasticity implicit in θ_C; numerical results here are only illustrative). We denote this landscape as (47k, 49k); that is, bimodal with peaks resulting in profits of $47k/month and $49k/month for the CMin and IMax strategies, respectively. Profitability falls off when high compensation is combined with low task richness and vice versa.

<Insert figure 2 around here>

As the simpler model indicated, the emergence of two peaks is rooted in the complementarity between task richness and employee quality. The relationships in the detailed model strengthen those complementarities due to the role of service capabilities and the reinforcing loops. Capabilities, by giving quality employees more opportunity to contribute, increase the complementarity between task richness and employee quality. Furthermore, the rewarding environment (R1), preserving knowledge (R2), and learning (B1) loops reduce the costs of maintaining a quality workforce. Each of these effects is small, but they add up and synergize, making IMax competitive with CMin with conservative parameters. Moreover, at high task richness, the various benefits of quality employees (e.g., higher productivity (see Eq. 1), margin, and capability building) limit the profitability tradeoffs on the compensation axis, creating a rather flat landscape: more compensation costs more, but also has multiple benefits.

Robustness and boundary conditions for a bimodal landscape. Three sets of analyses (see Appendices A4–A6 for detailed analyses) inform the robustness of these results. First, we show that the landscape remains bimodal even if we include all managerial decisions (we didn't include μ, which is only relevant with stochastic demand) as strategic levers. In two other analyses, we first individually change all key model parameters and compare the resulting profitability of the two local peaks to inform the factors affecting the relative strength of each strategy. We also conduct a multidimensional sensitivity analysis and examine the shape of the performance landscape in the more distant points in the parameter space. These results also find no more than two local peaks across more than 1,000 landscapes, each potentially representing a distinct market or industry. However, an unexpected third *type* of local peak, which we call "volunteer-based," emerged. It includes low compensation and high task richness and becomes relevant when employees are not sensitive to compensation but otherwise their quality is beneficial.

Overall, IMax peak gets a boost through different channels, including (a) enhancing the direct benefits of employee quality (e.g., services in which engagement and skills can enhance sales, margin, or capacity); (b) strengthening reinforcing feedbacks (e.g., impact of colleagues on job attractiveness); (c) reducing the costs of employee quality (e.g., stronger learning effects or higher employee-quality elasticity to compensation); and (d) increasing the costs of low-quality employees (e.g., high turnover cost and turnover sensitivity to job attractiveness). When these effects are strong enough, the bimodal landscape becomes unimodal with a single IMax peak. On the other hand, CMin is strengthened when employee quality is moderately sensitive to compensation, (a) task richness is bounded from above, (b) capital is not important (and thus capability benefits cannot be leveraged), or (c) both direct and feedback-based benefits of employee quality are small.

A bimodal landscape is robust and not so complex that the large number of other peaks would render the discovery or imitation of IMax infeasible. In addition, even with conservative parameters, IMax can be as profitable as CMin. Why, then, is IMax not more widely adopted? Three answers emerge:

Contextuality: A barrier to adoption of interdependent strategies. Part of the answer may lie in the relative sensitivity of different peak locations to environmental contexts. Here, the exact location of IMax peak relies on interacting effects, while CMin strategy is a robust local peak whether a particular effect exists or not. Thus, CMin provides a simple target for replication and imitation while IMax requires fine-tuning multiple choices to the context. Prior models have shown that imitation becomes ineffective when environmental contexts change significantly (Csaszar and Siggelkow 2010); here, we show that even if the environment is steady, firms may face strategies with different levels of contextuality. Such asymmetry promotes those strategies that are similar across different contexts and undermines the more contextual ones. To illustrate, consider the separate and combined effects of three subsets of relationships and how the landscape changes from the base case (47k, 49k) at compensations (1000, 4200) $/month. First, if we increase the costs of building employee quality by removing learning and onboarding/training benefits, the new payoff landscape will have the bimodal profitability peaks (53k, 47k) at compensation levels (1000, 4800) $/month for CMin and IMax. While similar to the base case, the CMin strategy now slightly outperforms the IMax: removing learning and training requires more compensation to get the same quality level for IMax peak while, for those following CMin, avoiding the costs of onboarding makes that strategy more profitable. Second, we remove all factors contributing to the intrinsic attractiveness of the job (zeroing the impacts of environment, task richness, and schedules). The new landscape, still bimodal, shifts to (49k, 47k) at compensation levels (1000, 2800). The major shift in IMax compensation reveals a synergy among contributors to job attractiveness. When compensation, task design, schedules, and environment come together to enhance employee quality, each extra unit of quality comes at a lower cost, making its benefits (for capacity, capabilities, and margin) worth those costs and pushing for compensation high enough to reach maximum quality. Absent nonmonetary contributors, raising employee quality is expensive, so marginal costs equal marginal benefits at lower compensation levels. On the other hand, the CMin strategy is boosted compared to the baseline, because the *rewarding environment* loop hurts CMin and, in its absence, employee quality increases in that peak. Finally, if we combine the effect of these two parameter changes and zero the effect of employee quality on margin ($\delta_Q=0$), we get a unimodal landscape dominated by CMin.

The key observations across these experiments are that (a) IMax's effectiveness relative to CMin depends on processes that regulate the costs of building employee quality and service capabilities and (b) the IMax peak configuration is sensitive to the strength of those processes. For example, IMax monthly compensation ranged between $2800 and $4800 in these simulations. Potentially more importantly, maximizing task richness, while easy in a model, is very contextual in practice. Task richness involves multiple practices whose relevant components and levels of importance are not known ex-ante. How much onboarding and training are sufficient to build employee quality? How much flexibility should employees have in solving customer problems, adapting the environment to local conditions or deviating from standard processes? The answer is contextual. For example Costco does not allow employees to order inventory to customize to local conditions but Mercadona and QuikTrip do. Whereas QuikTrip doesn't allow employees to customize product displays for local customers but Costco does. Moreover, given the relative flatness of the profit surface with respect to compensation at high levels of task richness (See right side of Figure 2), firms may adopt IMax while having significantly different compensation levels. IMax therefore eludes a universal blueprint, may include significant variations across successful examples, and requires customization by competent management (Sadun et al. 2017). Moreover, once adopted, this strategy must be fine-tuned as the environment changes, further complicating its maintenance. CMin, in contrast, has a simple template: minimize task richness to design out the risk of costly employee errors, then hire anybody willing to work for the minimum wage and with unstable schedules. Even when it is not the best option, CMin is easier to find, imitate, and maintain.

Robustness and generalizability. Strategies are more contextual when they rely on complementarities (Siggelkow 2002b). In our setting (and, we suspect, in many others) reinforcing loops are an important driver of complementarity and, as such, a possible source of contextuality for strategies that depend on them. Assessing the role of reinforcing loops in promoting alternative strategies is therefore important in deciding whether contextuality is a relevant mechanism in a new setting.

Temporal complexity of adopting IMax. Temporal complexity is a second barrier we found to adopting IMax. In practice, there is no ex-ante formula to accurately predict IMax's viability in a new setting. Organizations need to experiment with new configurations to learn about potential benefits and costs of

IMax. We investigate such experiments by simulating managers adopting IMax in a setting in which it is clearly more profitable than CMin (47k, 64k) (see Appendix A5 for parameterization). We consider three moves on the strategy space. In the first two, the organization starts from a configuration different from IMax in compensation or task richness in Panels A and B respectively. That choice is then changed from its inefficient value to the IMax value, completing a move to IMax. In the third, we model a move changing both choices to move from the CMin peak to the IMax peak. In discussing the results (reported in Figure 3), we consider what managers observe and learn in such experiments.

In Panel A, the firm starts with a task richness of 0 and the compensation appropriate to IMax peak. The firm is moderately profitable: well-paid, quality employees have significant benefits in terms of margin and building a rewarding environment, yet without task richness, other benefits of employee quality are forfeited. At time 5, task richness is raised to 1, which completes the transition to IMax. As a result, a few new employees (or consultants) are hired (dashed line) to build the required capabilities (dash-dot line). The costs of building capabilities—mostly labor costs—significantly reduce profitability until the build-up of capabilities is completed and the long-term employee level is reached. In practice, because transition to IMax requires building employee trust through no-layoff policies, the labor reduction should be due to either the departure of transient workers brought in for capability building period (such as consultants) or natural turnover (often high amid organizational transitions). This worse-before-better dynamic is a salient feature of such moves.

<Insert figure 3 around here>

A similar tradeoff emerges in shifting from the moderate compensation at CMin ($1720/month, due to high δ_Q) to the higher level ($2830/month) required for IMax (Panel B). Costlier employees initially reduce profits and shift the mix of labor and capital towards more capabilities, accounting for the transient increase in capability. Profitability recovers when employee quality has reached its new equilibrium, but this is a slow process relying on endogenous effects of Rewarding Environment (R2) and Learning (B2) loops. Finally, in Panel C, our simulated manager moves both strategic levers from the CMin peak to IMax one. The resulting combination of high short-term costs of building capabilities and slow endogenous build-up of employee quality creates a substantial worse-before-better dynamic.

Smarter transition pathways could reduce the performance dip, but none in our model could avoid a short-term drop due to the investments needed to build key stocks (capabilities and employee quality) and their slow, endogenous buildup due to feedback effects. Organizational experiments may therefore be misleading. If worse-before-better tradeoffs are not foreseen and correctly accounted for, managers learn from hard numbers in early feedback that IMax is not viable in their industry—or worse, that it is just a high-minded fad—and terminate programs before measurable benefits can justify the costs. One needs to believe in IMax's long-term viability and to invest in it knowing that there will be short-term losses. Mud Bay, for example, saw a dip in profitability for a couple of years, but this was expected and management remained committed. During Quest Diagnostics' transition to IMax from CMin turnover increased even for higher-paid employees, due to the higher demands of the job, before it started decreasing.

Robustness and generalizability. The temporal complexity mechanism depends on delays—in building the required stocks (e.g., capabilities and employee quality) and in building up synergy among feedback loops—and on whether those delays are similar to or larger than organizational measurement, attention, or review cycles. For example, in our context, the time needed to build capabilities and endogenously develop employee quality varies from months to years, comparable to or larger than quarterly or even annual organizational review cycles. The effect of slow-moving feedback synergies is especially hard to detect in practice. For example, in Figure 3-C, the slow but substantial increase in profits between months 20 and 70 results from feedback loops and is critical for the correct appraisal of IMax.

Sustaining IMax in the face of variable demand. Most products and services are subject to seasonal, weekly, and daily demand variations. Manufacturing firms can buffer against demand variability using inventories in production and supply chains, but service firms have to meet demand when it occurs. So they try to match labor supply to customer demand by changing employee hours. They often provide employee schedules a week or less in advance and, even so, can make last-minute changes. This significantly reduces job quality and increases turnover, thus reducing returns on investments in human capital or involvement (Henly and Lambert 2014). This challenge distinguishes the implementation of IMax in mass market services from that in manufacturing. We use the demand noise, N, with a weeklong auto-correlation time to explore the impact of short-term demand variability.

<Insert Figure 4 around here>

Employee adjustment time (μ) is the lever controlling how management adjusts the workforce to demand. A small μ is the norm in mass market services, indicating quick matching of employee hours with demand. Large μ indicates more stable schedules and slower matching of workforce to demand.

Responsiveness to customer demand versus job attractiveness—and thus employee quality—creates a tradeoff, which we analyze by replicating the baseline graph for two scheduling strategies under variable demand: In the rapid adjustment scenario (Figure 4-A, μ=2 days), the firm quickly matches employees to demand fluctuations. The alternative, stable scheduling, is captured in Panel B (μ of 1 month).

With the rapid adjustment, demand variability hurts IMax more than CMin (Panel A; with peaks of (38k, 32k)). Employee quality drops when firms chase demand, reducing profits across the board (compared to the deterministic base case). However, the IMax peak is compromised more severely because it depends on recruiting and maintaining quality employees—difficult with unstable schedules. Switching to stable scheduling boosts the IMax peak significantly (Panel B, leading to peaks at (37k, 43k)). A new mechanism explains the interaction between scheduling policy and the dominant strategy. With high task richness, the firm needs its people to maintain organizational capabilities, so that these capabilities act as buffers: when demand exceeds the available workforce's capacity, employees can be diverted from capability-building activities to customer service. In practice, capability buffers span not only capability building but also various non-customer-facing tasks such as maintenance, training, delivery, inventory processing, and timing of promotions and new product introductions. Capabilities are inertial, so temporary rebalancing does not undermine them and is balanced out when, at times of low demand, employees double down on capability building. Over time, capabilities absorb the demand variability, enabling reliable service with stable schedules. In fact, with slow adjustment, even CMin benefits from some capability buffer (the CMin peak in Panel B appears at β=0.1).

In practice, implementing capability buffers requires conscious effort. Mercadona uses inventory upkeep, shelving, maintenance, and communication and testing of process improvement ideas to create these buffers. Costco staggers new product introductions to smooth store workload. Interestingly—and consistent with some recent findings (Williams et al. 2018)—we observed that schedule uncertainty is induced not only by demand, but also by headquarters, due to long delivery windows, discrepancies between planned and actual deliveries, and last-minute changes to promotions and products. Thus, headquarters can actively reduce workload variability and the need for unstable schedules.

Robustness and generalizability. Unstable schedules complicate the adoption of IMax strategies in service operations exposed to demand variability. In those settings, capability buffers are effective when (a) there are enough non-customer-facing activities to make buffers sufficiently impactful and (b) the time constant for demand variability is shorter than that for capability dynamics, so that using buffers does not erode capabilities significantly (Rahmandad et al. 2018). Typically, buffering strategies can smooth out daily and weekly variations in demand but larger and more persistent seasonal variations (which we did not model in *N*) often require other responses, such as the use of part-time employees.

DISCUSSION

Viewing mass market service firms as interdependent choice systems, we modeled their performance landscape from the bottom up and found that complementarity among employee quality and task richness can create two distinct, locally dominant strategies. The plausibility of bimodal landscapes in light of complementarity among human resource practices has long been recognized, especially in manufacturing (Ichniowski et al. 1997; Jiang et al. 2012; Kochan and Osterman 1994; Macduffie 1995; McGregor 1960). However, these accounts did not distinguish between positioning and bimodal landscapes when serving the same market segment. In fact, research often views the two strategies to be fitting different segments (Arthur 1992; Porter 1996), so that IMax could be dismissed as irrelevant for much of the economy. We show that bimodal landscapes may well exist in targeting mass market services, which is promising for IMax's relevance beyond niche markets. Now, however, we have to ask: why isn't IMax more widely adopted? This question may resonate beyond our empirical context; for example, lean methods are thought to be underutilized (e.g., Bhamu and Sangwan 2014; Shah and Ward 2003). By studying this question in the context of mass market services, we also contribute more broadly to theory on the complexity of adopting alternative strategies. Here, we start with the existing theory on sources of complexity that underlie heterogeneous strategies and how two of the mechanisms we analyzed—contextuality and temporal complexity—complement existing theory. We then expand on the prospects for better jobs in mass market services, including discussion of our third mechanism—instability of schedules in services.

Combinatorial complexity. A leading explanation for heterogeneity in strategies builds on the large number of local peaks on rugged performance landscapes (Levinthal 1997). At its core, this argument is about combinatorial complexity making the task of finding optimal organizational configurations infeasible (Rivkin 2000). Our study bridges this theoretical view with empirically grounded operational relationships, providing support for multi-peaked landscapes while elaborating on their features. Specifically, existing NK formulations include a multitude of local peaks (Rivkin 2000), yet we find no more than two in our model. Adaptation is difficult even with two (Busemeyer et al. 1986), but may be qualitatively different than it is with hundreds.

One cannot generalize from a single case-based study to the general shape of performance landscapes, yet our methods offer a way to close the gap between theory and empirics. The broader insight from our simple model may be that complementarity adds order to the performance landscape and promotes as local peaks configurations that either share all complements or lack them all (Rahmandad 2019). This finding can refine intuitions about the determinants of ruggedness, where some (but not all; see, for example Porter and Siggelkow 2008; Rivkin 2000) have suggested that complementarity may induce ruggedness (e.g., Dosi and Marengo 1999; John and Saloner 2013). Thus, the frequent observation of complementarity among managerial choices (Ennen and Richter 2010) may give us pause in expecting very rugged landscapes due to combinatorial complexity. Where local optima are limited to a handful, combinatorial complexity alone cannot explain the observed heterogeneity in strategies, imitation challenges, and inefficiencies. Our theory-building exercise elaborates on two other sources of complexity that complement existing accounts: contextuality and temporal complexity.

Contextuality. Our analysis highlights that a strategy's context-sensitivity—that is, the complexity due to contextuality—matters in its adoption (Porter and Siggelkow 2008). For example, IMax peak may exist and have a large basin of attraction, but its exact configuration—for example, its optimum compensation or how to increase task richness—is sensitive to the environmental context in which it is implemented. Three distinct flavors of contextuality can be identified. First is the sensitivity of the location of a local strategy peak to context. In our setting, the optimal IMax compensation is more sensitive than CMin's to the specific parameters defining the environmental context. This mechanism aligns with Siggelkow's (2002b) insight that misperceiving complementary interactions is more costly than misperceiving substitution effects. The second variant of contextuality relates to the detailed content of strategies at a given peak. Leveraging complementarities and reinforcing feedback loops for a strategy (say, IMax) entails designing work processes that realize the benefits of those interdependencies, which in turn requires fine-grained process optimization. Strategies that do not rely on such complementarities are easier to modularize into independent components that can be standardized and applied across contexts. A case in point is the content that goes into maximizing task richness in our setting, which would vary in its details from business to business even if the broad idea were the same. Both these dimensions of contextuality require managers to invest in discovering the effective configuration for each application. A third mechanism builds on the first two: firms already following a contextual strategy (e.g., IMax) point to different targets (e.g., in compensation or in the specifics of task richness), which erodes the confidence of would-be imitators in the existence of a viable IMax strategy. Flatness of landscape with respect to compensation in the vicinity of IMax (See Figure 2) further adds to potential for variance in targets of imitation. Less contextual strategies (e.g., CMin), in contrast, provide a clear and replicable template that simplifies adoption, imitation, and maintenance. This view of contextuality builds on prior research by elaborating on its features, quantifying it within an empirically motivated model, putting forward feedback loops as a useful analytical lens for formalizing contextuality, and highlighting that different strategies may vary in their contextuality and thus that the concept informs the frequency of adoption of competing strategy in the same market.

Temporal complexity. Common conceptions of performance landscape map *expected* performance as a function of each strategic choice. Implicit in that conception is the idea that every move on the landscape is followed by unbiased (even if noisy) feedback on the long-term performance of that choice. In practice, temporal complexity kicks in when changes in strategy are followed by transient dynamics that may provide biased—even misleading—performance feedback. We show how the building and erosion of resources—such as employee quality and service capabilities—combined with feedback effects can generate misleading transient dynamics. These dynamics are more acute for some strategies than for others, may last longer than organizational evaluation and change cycles, and are often underestimated by managers (Humphreys et al. 2016). Thus, a gap is created between the transient performance gradient perceived by managers and the steady-state ones that create the basins of attraction common in the literature. This gap results in adaptation challenges we call temporal complexity. For example, the worse-before-better dynamic can mislead managers, engender faulty mental models, and trap managers in low-performing regions of the strategy space. Thus, temporal complexity not only can induce heterogeneous adaptation trajectories (Fang and Levinthal 2009; Rahmandad 2008), but also create biases in favor of specific strategies; for example, in our context, CMin. Temporal complexity also creates incentive misalignments across organizational levels (which we did not formally model). For example, if middle managers are expected to be the change agents to seek IMax, they may not want to bear the costs of transition in return for uncertain outcomes. Thus, in most large service chains, a strong commitment from top management would be necessary to start the transition to IMax. On the other hand, the sustained collaboration of managers at headquarters and frontline managers is indispensable for actual changes in task richness and for stable schedules. The complexity of such multi-level change processes could be another barrier to the transition to IMax. More generally, temporal complexity points to a broader definition of performance landscape, one in which transient outcomes are explicitly modeled and adaptation requires grappling with the credit assignment problem (Minsky 1961). Such extension would better align theories of organizational adaptation with the actual challenges faced by managers.

Practical implications

Convenience stores and supermarkets, among other low-cost retailers, are known for focusing on CMin in light of fierce competition, thin margins, and limited customization opportunities. Employees are often paid close to minimum wage with limited benefits and unstable schedules; high turnover is the rule (Carre et al. 2010). However, cases such as Costco, Mercadona, Trader Joe's, and QuikTrip suggest that IMax peak can coexist with—and even outperform—labor-cost minimization in these settings. For example, these firms all have higher productivity of their three important assets (employees, space, and inventory) than their competitors and some have higher profitability. Our model supports those case-based observations by formalizing the mechanisms that lead to a bimodal landscape, but also highlighting some of the challenges in adopting IMax of which managers need to be aware.

We also observed advantages in adopting IMax that we did not build into the model, but are relevant for managerial consideration. First, IMax provides customers with better service and experience and thus builds loyalty. It can therefore be easily adapted to more quality-sensitive market segments, enhancing profits through higher margins and less competition. Second, we assume good decision making by all CMin and IMax managers. But we observed that, in CMin environments with high employee turnover and frequent callouts, managers face frequent emergencies and find little time to think, plan, teach, or lead; IMax is more amenable to better management and operational excellence. One store manager at a CMin supermarket told us: "Between maintenance issues and checking out customers [due to understaffing], I did almost no training, no performance management….hired the wrong people….I could think of a hundred things to improve… but never had the time." Third, IMax can offer firms dynamic capabilities that are critical in the face of environmental change (e.g., in technology, customer needs, regulations) when involved employees help identify such trends early, devise responses, test solutions quickly, and roll out promising adjustments. For example, during the 2008 economic crisis, Mercadona was able to reduce prices by 10%—and hence gain market share—largely due to cost-saving improvements suggested by store employees. Fourth, companies following IMax can offer a wider range of compensation than CMin competitors while sustaining profitability (See Figure 2). This feature offers IMax firms flexibility, and also enables them to push for and benefit from higher minimum wages and scheduling legislation. In contrast the CMin competition is negatively affected by such regulations.

Given these potential upsides of IMax, one practical contribution of our work is in clarifying the managerial levers to enable the strategy and the expected tradeoffs. The more traditional human resource factors—including higher and performance-based compensation, training, and job security—remain important; we highlight a second set of levers summarized in task richness. The two go hand in hand, so enhancing job quality without task richness may pay little financial dividend. The components of task richness will vary depending on the business; in retail, for example, task richness increases with enabling employees to learn about products, perform customer-facing and non-customer-facing tasks, use discretion to solve customer problems, take part in improvement, and offer a smaller product selection (to enable the previous levers). With some large service firms attempting to improve job quality (Prokesch 2017), this consideration is critical for enhancing their bottom lines and avoiding disappointment.

Apart from contextuality and temporal complexity, we identified an important practical challenge to IMax: variable demand with no inventory buffers in services often leads to unstable employee schedules that drive quality employees away. This mechanism provides an explanation for the divergence in IMax adoption between the manufacturing, which includes inventory buffers, and where IMax variants have been more widely adopted (Osterman 2000), and mass market services. We also find that capability buffers can shield the workforce against variation in customer traffic, providing more stable schedules and job security and thus reclaiming IMax. In practice, implementing capability buffers requires cross-training, insourcing cleaning and maintenance, increased use of capabilities (requiring continuous investments), and smoothing workload through careful scheduling of deliveries, product introductions, promotions, display changes, training, and other non-customer-facing activities. We have observed that these practices are under-used because they require coordination among functions. In retail, for example, deliveries are often the province of logistics, promotions and product introductions are often determined by merchandising, displays are often designed by visual departments, store labor budgets are set by finance, and frontline managers are in charge of allocating hours and coordinating all store activities. Using capability buffers to improve schedule stability requires coordination among these compartmentalized actors.

Finally, some feedback loops at the heart of IMax could be strengthened by design and managerial action. Community events may strengthen the “Rewarding Environment” loop and rapid standardization of improved processes can enhance the value of quality employees for capabilities. Building IMax thus requires management to design operations with an eye on task richness, stable schedules, and strengthening the feedbacks that support quality employees.

IMax also entails strategic tradeoffs. It moderates a service company’s feasible and optimal growth rates. On the one hand, the delays involved in building capabilities and a high-quality workforce limit organic growth rates. But this doesn’t mean IMax is incompatible with growth. Mercadona became Spain’s largest supermarket chain, with over 1,600 stores and more than €20 billion in sales in 2017, and Costco was the world’s second-largest retailer in 2017. In fact, retaining high-quality employees often *requires* growth so that the best can be promoted and stock ownership programs remain attractive. These competing forces call for a tight balance in expanding operations: fast enough to motivate employees but not so fast as to compromise the building of a quality workforce and effective processes.

Another balancing act is combining task richness with process discipline. Empowering employees to customize customer service and to challenge existing processes should be designed carefully so as not to cause diseconomies. For example, before 2000, Home Depot stores had significant autonomy in merchandise selection, logistics, layout, inventory management, and customer service. This environment attracted quality employees but led to the proliferation of incompatible systems across stores, lack of bargaining power in the supply chain, low levels of automation, and complexity of implementing changes across stores; the end result was a reversal of strategy towards CMin. In contrast, Mercadona and QuikTrip actively standardized testing and dissemination of improved processes, so that innovations from one store could be assessed for wider adoption and quickly rolled out when proved effective. A complex part of adopting IMax is designing business processes that combine employee empowerment and process improvement with discipline in implementing new processes and in standardization.

Limitations and Future Research Opportunities

A few other mechanisms were relevant to understanding the adoption of competing strategies in our case data but did not make it into our formal model. First, CMin, by offering more certain, short-term, feedback, has an easier time gaining legitimacy and becomes the de-facto model in training new managers, designing measurement systems, and guiding investors' expectations. Second, the bias towards CMin may be imprinted into new firms as entrepreneurs and funders seek to maximize startup flexibility by using contract (rather than full-time) workers (the so-called 1099 vs. W2 debate) or to maximize growth. Third, sustaining IMax, once it is in place, rests on mutual trust among employees and management, which requires continuous nurturing and is vulnerable to environmental and institutional shocks and to turnover (Gibbons and Henderson 2012; Rubinstein and Kochan 2001).

Care should be taken in generalizing to other contexts. More comprehensive portrayals of performance landscapes in services and beyond could include (a) organizational considerations, such as distinguishing between establishment managers and line employees and between full-time and part-time workers, (b) replacing the assumption of rational managers and perfect execution with more realistic alternatives, (c) separating employee quality into motivation and human capital, (d) explicit representation of human resource practices such as pay for performance, (e) the benefits of some turnover, (f) supply chain, sourcing, and other operational functions that affect the amount and variability of the workload, and (g) positioning based on multidimensional performance in competitive markets (Adner et al. 2014). Empirical testing of the model's relationships and predictions is another promising direction. Finally, there is much room for the analysis of how firm-level dynamics interact with institutional and policy factors to shape not only firms' performance landscapes but also economy-wide patterns of job quality. A few relevant extensions include (a) capturing both the constrained labor pool and the incentive effects of firms adopting IMax on human capital acquisition by potential employees, (b) the impact of product and process innovation on the viability of IMax versus CMin (Womack et al. 1991), and (c) the impact of government policies, such as minimum wage and scheduling legislation, on a firm's calculus.

Conclusions

Our model-based study of mass-market services offers contextuality, temporal complexity, and variable demand with no inventory buffers as drivers of complexity in adoption of strategies. They can lead to faulty learning, biased diffusion, and erosion of profitable strategies. Our theory suggests that to explain heterogeneity in strategies among firms targeting the same market we do not need to resort to the NP-hardness of rugged performance landscapes (though that may be relevant in some settings). In fact even finding the local peak cannot be taken for granted and inefficient strategies may be reinforced, be imitated, and persist despite the occasional appearance of more promising alternatives. The resulting theoretical perspective also elevates the role of managers in management theory. Managers have opportunities to learn and transfer their knowledge if typical performance landscapes include only a handful of coherent strategies that may apply beyond a single organization, and if challenges to the adoption of effective strategies follow regular templates, such as worse-before-better tradeoffs. This shift further aligns our theoretical explanations for firm heterogeneity with the mounting empirical evidence on inefficiencies in—and the impact of—management practices (Bloom et al. 2019; Sadun et al. 2017). We hope by bringing together case data and rigor of formal models this paper contributes to building wider bridges between management theory and managerially relevant insights in mass market services.

REFERENCES

Adner, R., F.A. Csaszar, P.B. Zemsky. 2014. Positioning on a Multiattribute Landscape. *Management Science* **60**(11) 2794-2815.

Ager, D.L., M.A. Roberto. 2013. Trader Joe's. Harvard Business School Publishing.

Appelbaum, E., J. Schmitt. 2009. Review article: Low-wage work in high-income countries: Labor-market institutions and business strategy in the US and Europe. *Human Relations* **62**(12) 1907-1934.

Arthur, J.B. 1992. The Link between Business Strategy and Industrial-Relations Systems in American Steel Minimills. *Industrial & Labor Relations Review* **45**(3) 488-506.

Bamber, G.J., J.H. Gittell, T.A. Kochan, A. von Nordenflycht. 2009. Contrasting Management and Employment-Relations Strategies in European Airlines. *Journal of Industrial Relations* **51**(5) 635-652.

Batt, R. 1999. Work organization, technology, and performance in customer service and sales. *Ilr Review* **52**(4) 539-564.

Baumann, O., J. Schmidt, N.J.J.o.M. Stieglitz. 2019. Effective Search in Rugged Performance Landscapes: A Review and Outlook **45**(1) 285-318.

Bhamu, J., K.S. Sangwan. 2014. Lean manufacturing: literature review and research issues. *International Journal of Operations & Production Management* **34**(7) 876-940.

Bloom, N., E. Brynjolfsson, L. Foster, R. Jarmin, M. Patnaik, I. Saporta-Eksten, J. Van Reenen. 2019. What Drives Differences in Management Practices? *American Economic Review* **109**(5) 1648-1683.

Brusoni, S., A. Prencipe. 2006. Making design rules: A multidomain perspective. *Organization Science* **17**(2) 179-189.

Bureau of Labor Statistics. 2017a. Industry Output and Employment Projections. U.S. Bureau of Labor Statistics.

Bureau of Labor Statistics. 2017b. National Occupational Employment and Wage Estimates. U.S. Bureau of Labor Statistics.

Busemeyer, J.R., K.N. Swenson, A. Lazarte. 1986. An Adaptive Approach to Resource-Allocation. *Organizational Behavior and Human Decision Processes* **38**(3) 318-341.

Cable, D.M., D.B. Turban. 2003. The value of organizational reputation in the recruitment context: A brand-equity perspective. *Journal of Applied Social Psychology* **33**(11) 2244-2266.

Carre, F., C. Tilly, M. van Klaveren, D. Voss-Dahm. 2010. *Retail Jobs in Comparative Perspective*.

Chen, C.X., T. Sandino. 2012. Can Wages Buy Honesty? The Relationship Between Relative Wages and Employee Theft. *Journal of Accounting Research* **50**(4) 967-1000.

Chuang, H.H.C., R. Oliva. 2015. Inventory record inaccuracy: Causes and labor effects. *Journal of Operations Management* **39-40** 63-78.

Csaszar, F.A., N. Siggelkow. 2010. How Much to Copy? Determinants of Effective Imitation Breadth. *Organization Science* **21**(3) 661-676.

Dess, G.G., J.D. Shaw. 2001. Voluntary turnover, social capital, and organizational performance. *Academy of Management Review* **26**(3) 446-456.

Dosi, G., L. Marengo. 1999. The co-evolution of technological knowledge and corporate organizations 15-23.

Ennen, E., A. Richter. 2010. The Whole Is More Than the Sum of Its Parts-Or Is It? A Review of the Empirical Literature on Complementarities in Organizations. *Journal of Management* **36**(1) 207-233.

Fang, C., D. Levinthal. 2009. Near-Term Liability of Exploitation: Exploration and Exploitation in Multistage Problems. *Organization Science* **20**(3) 538-551.

Fleming, L. 2001. Recombinant uncertainty in technological search. *Management Science* **47**(1) 117-132.

Forrester, J.W., P. Senge. 1980. Tests for building confidence in system dynamics models. A. Legasto, J.W. Forrester, J.M. Lyneis, eds. *System Dynamics. TIMES Studies in the Management Sciences 14*. North-Holland, New York, 209-228.

Gibbons, R., R. Henderson. 2012. Relational Contracts and Organizational Capabilities. *Organization Science* **23**(5) 1350-1364.

Hackman, J.R., G.R. Oldham. 1975. Development of the job diagnostic survey. *Journal of Applied Psychology* **60**(2) 159.

Hatch, N.W., D.C. Mowery. 1998. Process innovation and learning by doing in semiconductor manufacturing. *Management Science* **44**(11) 1461-1477.

Henly, J.R., S.J. Lambert. 2014. Unpredictable Work Timing in Retail Jobs: Implications for Employee Work-Life Conflict. *Ilr Review* **67**(3) 986-1016.

Homer, J. 2019. Best practices in system dynamics modeling, revisited: a practitioner's view. *System Dynamics Review* **35**(2) 177-181.

Humphreys, K.A., M.S. Gary, K.T. Trotman. 2016. Dynamic Decision Making Using the Balanced Scorecard Framework. *Accounting Review* **91**(5) 1441-1465.

Ichniowski, C., K. Shaw, G. Prennushi. 1997. The effects of human resource management practices on productivity: A study of steel finishing lines. *American Economic Review* **87**(3) 291-313.

Jiang, K.F., D.P. Lepak, K.J. Han, Y. Hong, A. Kim, A.L. Winkler. 2012. Clarifying the construct of human resource systems: Relating human resource management to employee performance. *Human Resource Management Review* **22**(2) 73-85.

John, R., G. Saloner. 2013. Strategy and Organization. R. Gibbons, J. Roberts, eds. *Handbook of Organizational Economics*. Princeton University Press, 799-849.

Kochan, T.A., P. Osterman. 1994. *The mutual gains enterprise : forging a winning partnership among labor, management, and government*. Harvard Business School Press, Boston.

Lambert, S.J. 2008. Passing the buck: Labor flexibility practices that transfer risk onto hourly workers. *Human Relations* **61**(9) 1203-1227.

Levinthal, D.A. 1997. Adaptation on rugged landscapes. *Management Science* **43**(7) 934-950.

Ling, T.K., C.K. Lee, W. Ho. 2009. The analysis and case studies of successful express logistics companies. *International Journal of Value Chain Management* **3**(1) 20-35.

Macduffie, J.P. 1995. Human-Resource Bundles and Manufacturing Performance - Organizational Logic and Flexible Production Systems in the World Auto Industry. *Industrial & Labor Relations Review* **48**(2) 197-221.

Mas-Colell, A., M.D. Whinston, J.R. Green. 1995. *Microeconomic theory*. Oxford University Press, New York.

Mayfield, M. 2010. The business of caring: Ararat nursing facility. Paraprofessional Health Care Institute and Hitachi Foundation, Washington D.C., and New York.

McGregor, D. 1960. *The human side of enterprise*. McGraw-Hill, New York,.

Milkovich, G.T., J.M. Newman, B.A. Gerhart. 2014. *Compensation*, 11th ed. McGraw-Hill/Irwin, New York.

Minsky, M. 1961. Steps towards artificial intelligence. *Proceedings of the Institute for Radio Engineers* **49**(1) 8-30.

Osterman, P. 2000. Work reorganization in an era of restructuring: Trends in diffusion and effects on employee welfare. *Industrial & Labor Relations Review* **53**(2) 179-196.

Pil, F.K., J.P. MacDuffie. 1996. The adoption of high-involvement work practices. *Industrial Relations* **35**(3) 423-455.

Ployhart, R.E., T.P. Moliterno. 2011. Emergence of the Human Capital Resource: A Multilevel Model. *Academy of Management Review* **36**(1) 127-150.

Porter, M., N. Siggelkow. 2008. Contextuality within activity systems and sustainability of competitive advantage. *Academy of Management Perspectives* **22**(2) 34-56.

Porter, M.E. 1996. What is strategy? *Harvard Business Review* **74**(6) 61-&.

Prokesch, S. 2017. The Right Thing to Do. Harvard Business Review, https://hbr.org/2017/12/the-right-thing-to-do.

Rahmandad, H. 2008. Effect of delays on complexity of organizational learning. *Management Science* **54**(7) 1297-1312.

Rahmandad, H. 2012. Impact of Growth Opportunities and Competition on Firm-Level Capability Development Trade-offs. *Organization Science* **23**(1) 138-154.

Rahmandad, H. 2019. Interdependence, Complementarity, and Ruggedness of Performance Landscapes. *Strategy Science* **Ahead of Print**.

Rahmandad, H., R. Henderson, N.P. Repenning. 2018. Making the Numbers? "Short Termism" and the Puzzle of Only Occasional Disaster. *Management Science* **64**(3) 1328-1347.

Rahmandad, H., J. Sterman. 2012. Reporting Guidelines for Simulation-based Research in Social Sciences *International System Dynamics Conference*, Saint Gallan, Switzerland.

Raman, A., N. DeHoratius, Z. Ton. 2001. Execution: The missing link in retail operations. *California Management Review* **43**(3) 136-+.

Repenning, N.P. 2002. A simulation-based approach to understanding the dynamics of innovation implementation. *Organization Science* **13**(2) 109-127.

Rivkin, J.W. 2000. Imitation of complex strategies. *Management Science* **46**(6) 824-844.

Rivkin, J.W. 2001. Reproducing knowledge: Replication without imitation at moderate complexity. *Organization Science* **12**(3) 274-293.

Rubinstein, S.A., T.A. Kochan. 2001. *Learning from Saturn : possibilities for corporate governance and employee relations*. ILR Press, Ithaca.

Sadun, R., N. Bloom, J. Van Reenen. 2017. Why Do We Undervalue Competent Management? Great Leadership and Brilliant Strategy Won't Succeed without Operational Excellence. *Harvard Business Review* **95**(5) 120-127.

Sastry, M.A. 1997. Problems and paradoxes in a model of punctuated organizational change. *Administrative Science Quarterly* **42** 237-275.

Shah, R., P.T. Ward. 2003. Lean manufacturing: context, practice bundles, and performance. *Journal of Operations Management* **21**(2) 129-149.

Siggelkow, N. 2001. Change in the presence of fit: The rise, the fall, and the renaissance of Liz Claiborne. *Academy of Management Journal* **44**(4) 838-857.

Siggelkow, N. 2002a. Evolution toward fit. *Administrative Science Quarterly* **47**(1) 125-159.

Siggelkow, N. 2002b. Misperceiving interactions among complements and substitutes: Organizational consequences. *Management Science* **48**(7) 900-916.

Siggelkow, N. 2011. Firms as Systems of Interdependent Choices. *Journal of Management Studies* **48**(5) 1126-1140.

Sinha, K.K., A.H. Van de Ven. 2005. Designing work within and between organizations. *Organization Science* **16**(4) 389-408.

Smith, R.S. 1979. Compensating Wage Differentials and Public-Policy - Review. *Industrial & Labor Relations Review* **32**(3) 339-352.

Sterman, J. 2000. *Business dynamics: systems thinking and modeling for a complex world*, 1 ed. McGraw-Hill/Irwin, Boston.

Ton, Z. 2014. *The good jobs strategy : how the smartest companies invest in employees to lower costs and boost profits*. New Harvest Houghton Mifflin Harcourt.

Ton, Z. 2017. How to Build a Business on Good Jobs. *Harvard Business Review* **Online**.

Ton, Z., S. Harrow. 2010. Mercadona. Harvard Business School, Boston.

Torres, J.P. 2019. System Dynamics Review and publications 1985-2017: analysis, synthesis and contributions. *System Dynamics Review* **35**(2) 160-176.

Williams, J.C., S.J. Lambert, S. Kesavan, P.J. Fugiel, L.A. Ospina, E.D. Rapoport, M. Jarpe, D. Bellisle, P. Pendem, L. McCorkell, S. Adler-Milstein. 2018. Stable scheduling increases productivity and sales *The Stable Scheduling Study*. Center for WorkLife Law, http://worklifelaw.org/publications/Stable-Scheduling-Study-Report.pdf.

Womack, J.P., D.T. Jones, D. Roos. 1991. *The machine that changed the world : how Japan's secret weapon in the global auto wars will revolutionize western industry*, 1st HarperPerennial ed. HarperPerennial, New York, NY.

Figure and Tables

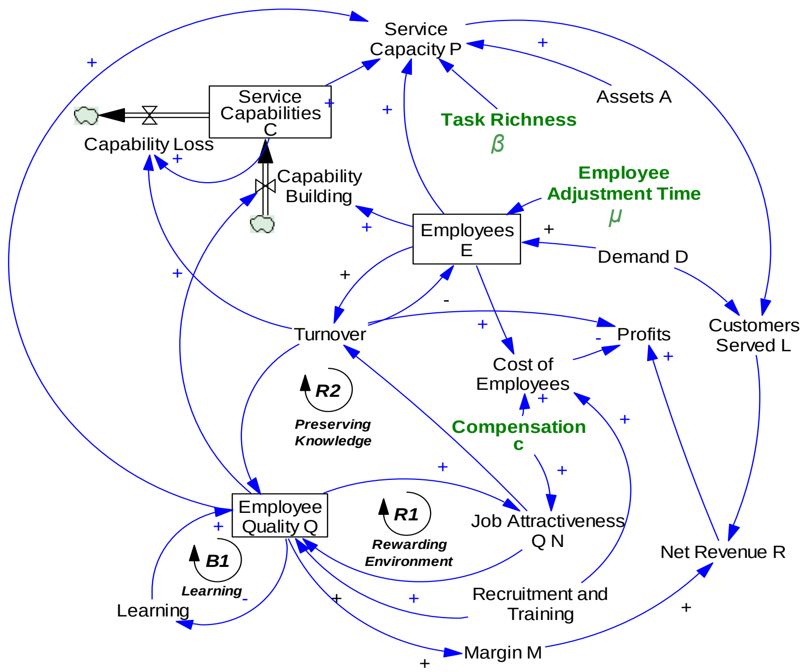


Figure 1. Overview of model processes. Stock (state) variables are depicted in rectangles.

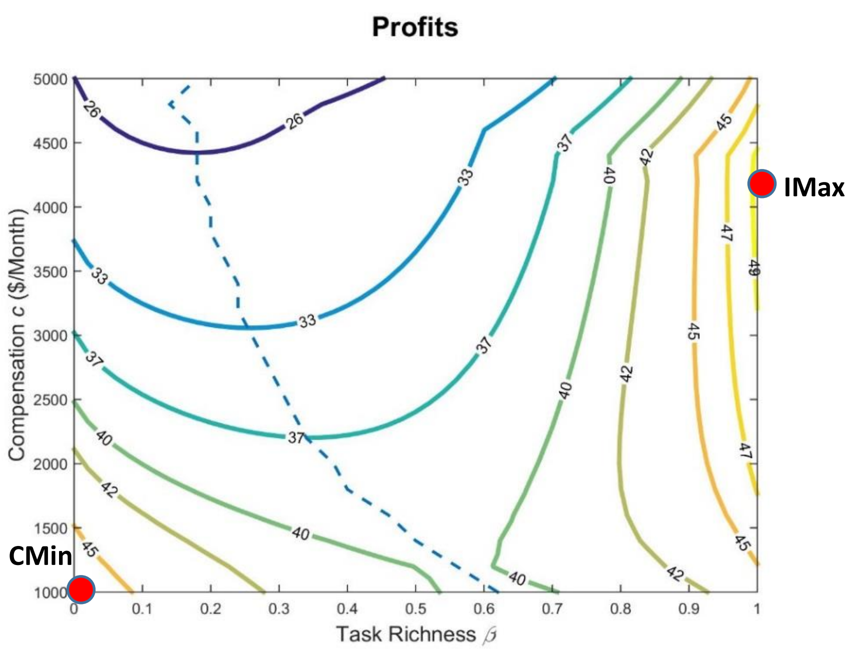
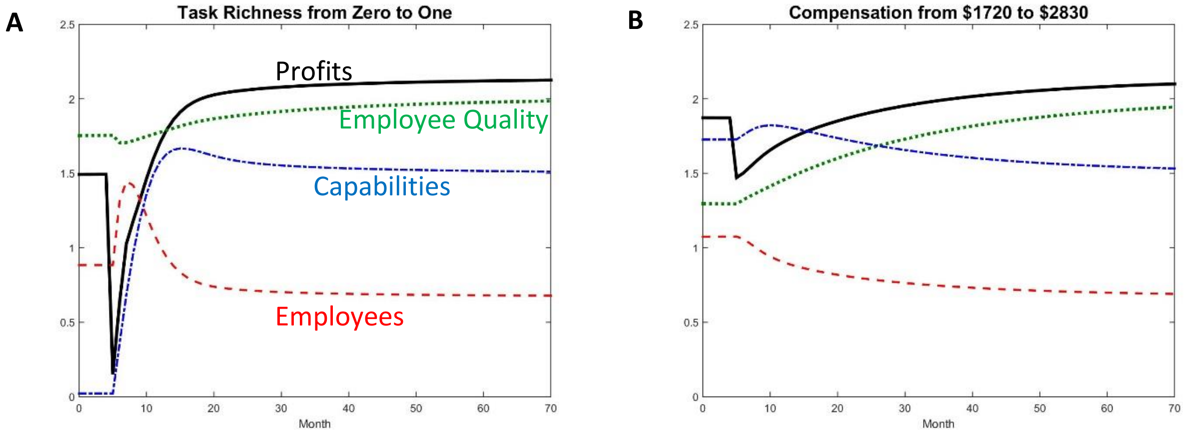


Figure 2. Profitability as a function of task richness and compensation. Contour plots reflect iso-profit curves. Two peaks emerge, one with low compensation and task richness (CMin strategy) and one with high compensation and task richness (IMax strategy). A dashed line separates the two basins of attraction for managers following local adaptation informed by expected performance outcomes.



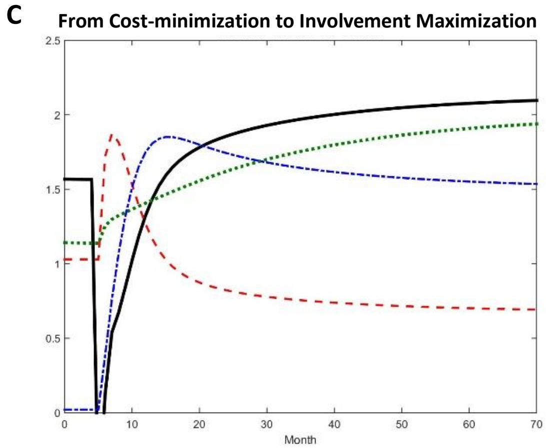


Figure 3. Transition dynamics for profits (in multiples of \$30k/month; black solid line), employees (in multiples of 10; red dashed line), employee quality (green dotted line), and capabilities (in multiples of two; blue dotted-dashed line) when transitioning to the IMax strategy peak. (A) Changing task richness from 0 to 1. (B) Changing compensation from \$1720 to \$2830 per month. (C) Changing both parameters from the CMin to IMax strategy peak.

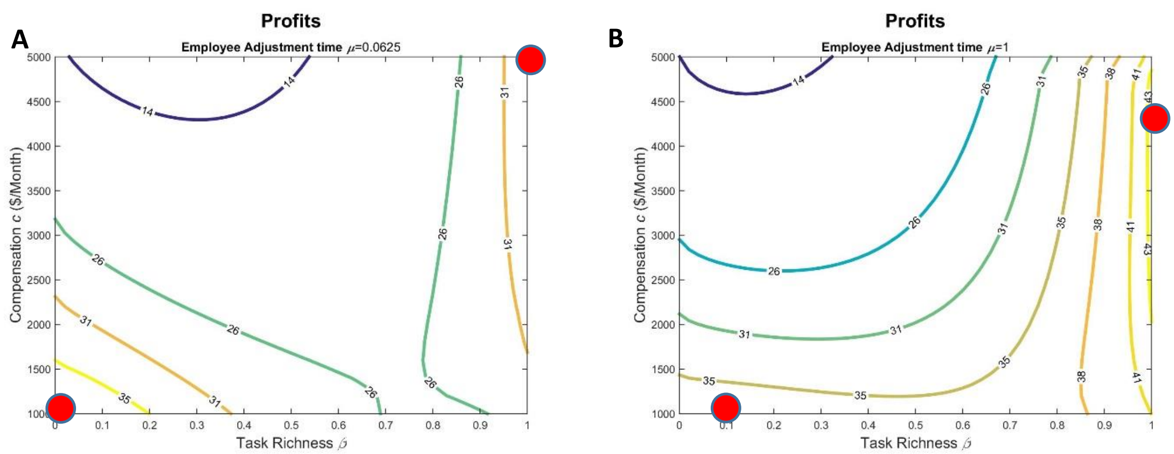


Figure 4. Expected long-term profit (in 1000 \$/month; averaged over 10 replications) as a function of compensation and task richness, under two scheduling scenarios: (A) Short adjustment time (μ=0.0625 months or ~2 days) indicates the JIT scheduling strategy. (B) Long μ (=1 month) indicates reliable schedules.

Online Appendices to accompany the paper:

If higher pay is profitable, why is it so rare?
Modeling competing strategies in mass market services

Contents

A 1- Model Documentation and Replication Instructions

The text of the paper and Appendix A2 provide the full model equations and explanation. This model was implemented in Vensim simulation software and is available as a Vensim Packaged Model (GenService-Simp-V15.vpm), included in the AnalysisCodesV15.zip. This zip file is available from the following link: https://osf.io/v4seb/?view_only=ea379b43a161496293f7b56ff79b42b1. You can open the model using the free Vensim Model Reader (http://vensim.com/free-download/), inspect the equations using the document tool ( ), and simulate the model using a single run or a synthesim ( ), in which simulation results are updated live with the changes to model parameters. You can inspect the simulated behaviors with the graph ( ) and table ( ) tools, among others.

The full replication of the analysis in the paper is more involved and requires many sensitivity analyses and optimizations. This was done using a Dynamic Link Library (DLL) connection that allowed us to control Vensim using MATLAB, submit various simulation tasks, and receive the results from Vensim in an automated fashion. Statistical analysis and graphing was done in MATLAB. The code for conducting this analysis is available in the attached MATLAB script, “genServiceAnal_V15.m,” and in various functions in “AnalysisCodesV15.zip.” The use of this code requires (a) access to the DSS version of Vensim and to MATLAB (32-bit to work with Vensim) and (b) setting up the DLL connection between the two programs. The instructions for this set-up are involved and go beyond the scope of this appendix, but the MATLAB code provides a full account of all the analysis reported in the paper and is easy to inspect. Moreover, this setup only facilitates, but is not required for, the replication of the analysis, which can be done without DLL connections.

A 2-Detailed model formulations

We start the full model documentation by repeating the equations from the simple model introduced in the main text to have all the equations in one place:

$P = \kappa C^{\alpha\beta} A^{\alpha(1-\beta)} {E_S}^{(1-\alpha)} Q^{(1-\alpha)\beta}$ (S1) P: Service Capacity

$Q = \left(\frac{c}{c_N}\right)^{\theta_c}$ (S2) Q: Employee Quality

$L = Min(P, D)$ (S3) L: Customers served

$D = d_b$ (S4) D: Demand

$R = LM$ (S5) R: Revenue

$M = m_b Q^{\delta_Q}$ (S6) M: Margin

$\pi = R - cE - c_{Fixed}$ (S7) π: Profits

In the equations above the use of a constant-return-to-scale capacity function is motivated both by general practice in other modeling efforts, and the fact that we wanted to exclude economies of scale from the strategy selection dynamics, since economies of scale may interact with quick-vs-slow strategies in complex ways (e.g., see Rahmandad 2012).

Next we introduce the equations capturing various effects discussed in the detailed model. Given their widespread application and simplicity we use multiplicative power functions (i.e. constant elasticities) to formulate various effects. This assumption has two potentially relevant implications: 1) The effects go to zero when input variables go to zero. Therefore when zero outputs are not realistic, one should be careful in interpreting results of a model operating in input regions close to zero. 2) Constant elasticities are often slow in capturing saturation effects and thus may lead to more extreme numerical results when operating in extreme regions of parameter space. Both potential issues may manifest when the model is operating in extreme values and not in the normal operating range. One can fix these robustness issues with more complex formulations, but given the generic nature of the model and lack of calibration to specific case data doing so would add much complexity with little empirical justification, so we opt for the simpler and more common formulations here. As a result we are careful not to report results where major inputs to various effects (e.g. employee quality or compensation) approach zero, or very large values.

To keep the presentation and discussion simpler the model discussed in the paper did not include the impact of service quality on various outcomes, however those mechanisms were salient in our case data, so we report on an augmented version of the model which includes those effects, but then set them to zero for the analysis. This setup provides a model that is more realistic and versatile for those interested in building on this work, but also remains easy to digest and is consistent with the analysis reported in the paper. The qualitative set of causal mechanisms in this augmented model are summarized in Figure S 1. As a result of including service quality and its impacts on job attractiveness and demand (see the following section), four new feedback loops are generated (B2 and R3-R5), even though they do not have any major impact on the analysis results. They are discussed below.

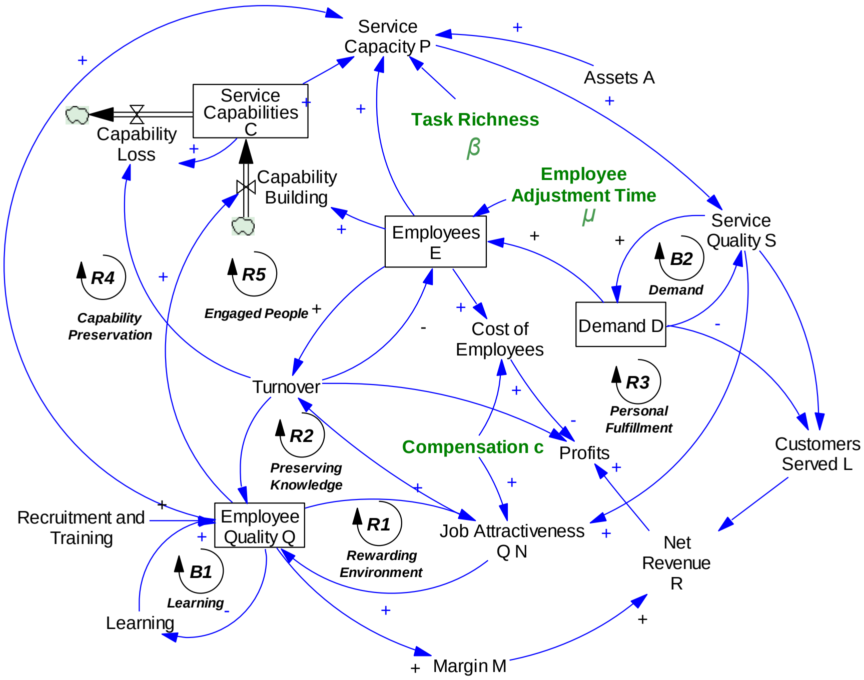


Figure S 1-Overview of model processes. Stock (state) variables are depicted in rectangles.

Customer and employee satisfaction-

Service quality (S) can be modeled as the ratio of service capacity (P) to demand (D) (eq. S8). We enhance demand formulation (eq. S4b) to be modified by uncertainty (N, a first-order auto-correlated noise with correlation time σ=0.25 months) around an underlying trend (D_u) that is anchored to a baseline (d_B: capturing overall market size) and slowly responding to service quality (eq. S9).

$S = \frac{P}{D}$ (S8) S: Service Quality

$D = D_U N$ (S4b) D: Demand

$\frac{dD_U}{dt} = \frac{d_B S^{\gamma_S} - D_U}{t_D}$ (S9) D_U: Underlying demand

To capture various contributors to employee quality we first make employee quality a stock that increases with the hiring of new employees based on the quality of recruits and changes endogenously through learning by doing. Quality of recruits (Q_O) depends on the quality of job applicants (captured in job attractiveness: Q_N) and initial screening and training of recruits (U): $Q_O = Q_N + U$. Below we provide more details on training and recruitment and its costs.

On the job learning is captured in the following equation:

$\frac{dQ}{dt} = \lambda e^{\rho(1-Q)}$ (S10) one the job learning

Where λ captures the strength of the learning effect and ρ the saturation speed and creates the balancing loop *B1: Learning*. Moreover, in practice employee quality is bounded and thus we limit Q to a maximum value, q_{Max}.

Job Attractiveness, Q_N is then modified based on compensation and other contributors to employee quality such as service quality (See S^{θ_S} term in eq. S15 below). Two other reinforcing loops (R1-Rewarding Environment and R2-Preserving Knowledge) emerge from considering the benefits of quality employees. We use the average current quality of employees (Q) as a proxy for the quality of the work environment and capture the Rewarding Environment feedback in Q^{θ_Q} term in job attractiveness (eq. S15). On the other hand Job attractiveness also influences voluntary turnover, creating a reinforcing loop (R3-Preserving Knowledge). We capture the average employee tenure (absent layoffs) to be bounded from below and adjusted around a baseline tenure τ_{V_b}:

$\tau_V = Max(\tau_{V\_min}, \tau_{V_b} {Q_N}^{\xi})$ (S11) τ_V=Employee tenure

Building and maintaining service capabilities- We follow previous research (Rahmandad et al. 2018) in modeling capabilities (*C*) as a stock that increases through investment (*I*) and erodes over time as a result of turnover, obsolescence of routines, and accumulation of random deviations.

$\frac{dC}{dt} = I - \frac{C}{T}$ (S12) C: Capability

We formulate capability building as a function of the number of employees allocated to this task (E_C), their normal productivity in building capabilities (e_c), and their quality (*Q*):

$I = e_c E_C Q$ (S13) I: Capability investment

We include the effect of turnover on capability erosion using the formulation:

$\mathrm{T} = \mathrm{t}_b J^{\varepsilon_\tau}$ (S14) T: Average capability life

Where $J = {Q_N}^{\xi}$ is the normalized turnover rate.

Direct determinants of job attractiveness- Schedules and job design are two other determinants of job attractiveness. Impact of schedule is activated when demand variability (*N*) is turned on (μ^{θ_μ} in eq. S15). Task richness's impact is included in the term $\left(1 - \theta_T(1-\beta)\right)$ which does not go to zero (for $0 \leq \theta_T < 1$) and therefore is robust in the full range for β. Thus, the complete determinants of job attractiveness are:

$Q_N = \left(\frac{c}{c_N}\right)^{\theta_c} Q^{\theta_Q} S^{\theta_S} \mu^{\theta_\mu} \left(1 - \theta_T(1-\beta)\right)$ (S15) Q_N: Job Attractiveness

Note that the impact of schedule variability, μ^{θ_μ}, will not be robust for extremely fast employee adjustment times (i.e. very small μ) when demand variability is active. Moreover, the ability of JIT scheduling to match demand depends on whether μ is smaller than the pink noise time constant, σ, in demand variability term (N) or not. As a result optimizing μ to maximize profit is dependent on the assumptions on demand variability and potential robustness issues at low levels of μ, and we therefore only reported results for high and low values of μ to provide qualitative insights without inducing undue certainty in numerical values of μ.

Training, recruitment, and turnover, and profits - The quality of incoming employees, Q_0, is modeled as the sum of job attractiveness (Q_N) and the quality impact of selective recruitment and initial training (*U*):

$Q_0 = Q_N + U$ (S16) Q_O: Incoming employee quality

The benefits of selective recruitment/training are modeled as the product of the per-person costs of training (C_T) and the return on training (R_U):

$U = C_T R_U$ (S17) U: Benefits of training

Per-person costs are anchored to efficient training ($C_T = c^*_T$). Return on each unit of training decreases with the amount of training offered (captured in parameter ζ), and is normalized using parameters c_{TN} (for normal costs of training) and *u* (training benefits given the normal cost). A value of ζ=-1 indicates such a strongly decreasing return that the benefits of training will not change with the amount of investment and a value of ζ=0 indicates that every unit of training cost increases quality by a fixed value with no decreasing returns.

$R_U = \frac{u}{c_{TN}} \left(\frac{c_T}{c_{TN}}\right)^{\zeta}$ (S18) R_U: Return on training

Next, the efficient training level is found by finding the training level that equates marginal quality return on training with marginal quality returns on paying employees more compensation, ensuring that the training strategy is consistent with the compensation strategy and current state of employees:

$$c_T^* = c_{TN}\left(\frac{Q_k \theta_C c^{\theta_C - 1}}{\frac{u}{c_{TN}}(1+\zeta)c_N^{\theta_C}\,\tau_{V_b}}\right)^{\frac{1}{\zeta}}$$ (S19) c^*_T: Efficient training cost

Where Q_k represents the quality indicated by factors other than compensation:

$$Q_k = \frac{Q_N}{\left(\frac{c}{c_N}\right)^{\theta_C}}$$ (S20) Q_k: Quality indicated without compensation

In the simulations, we use the following parameter values for this sector: ζ=-0.8; u=0.05; and c_{TN}=1600 \$/person.

Finally, profits are calculated as:

$$\pi = R - cE - \frac{C_T E}{\tau_{V_b} Q^{\xi}} - \frac{c_N}{e_C t_b a_A} A - c_{Fixed}$$ (S21) π: Profits

Here the first term is net revenue, the second is cost of compensation, the third is cost of employee recruitment and training, and the forth is the cost of assets. A fixed cost of C_{Fixed}=\$50,000 per month is also included in simulations.

Labor and Capital Investment Decisions- The model includes endogenous managerial decisions on how much capital and labor to acquire. These decisions are modeled to follow labor and capital levels that are profit-maximizing at given levels of demand, desired service quality, compensation, and task richness. Desired service quality, *s*, is a managerial choice that is not used in the main analysis, because by zeroing out the impacts of service quality on various outcomes the optimum level of *s* is always one (which is the value used in the baseline analyses). For the augmented model we explicitly consider this managerial lever which may, in some settings be set at values other than one. To calculate the rest of the decisions based on those three choices, we follow three steps:

1) Calculate unit employee cost, unit asset cost, and unit capability costs.
2) Calculate profit-maximizing budget, capital, capability, and employee levels.
3) Gradually adjust capital, capabilities, and labor towards their profit-maximizing values.

The formulations for these steps are discussed in more detail below. All formulations are also documented inside the full model.

Step 1)
Unit employee cost per month includes monthly compensation plus the employee's cost of hiring and training spread across the expected tenure for a given compensation:

$$C_E = c + (c_h + c_t)/Max(\tau_{V\_min}, \tau_{V_b}\left(\frac{c}{c_N}\right)^{\theta_c \xi})$$

c_h: Minimum hiring costs
c_t: Additional training and hiring costs, which help with finding/training better employees

Unit asset (human-independent capital) cost per month is anchored to the capability cost. It is calculated to include the cost of building one unit of capability with unit employee quality and normal capability life. This baseline cost is then adjusted with a parameter, a_A, signifying the relative cost advantage of assets. For comparability with other factors, asset costs are spread over time as rents:

$$C_A = \frac{c_N}{e_C t_b a_A}$$

a_A: asset cost advantage over capabilities

Unit capability cost accounts for the cost of employees needed to build one unit of capability (given current employee quality) and the current capability life:

$$C_C = \frac{C_E}{e_c Q \mathrm{T}}$$

Step 2)

Using the desired service quality, s, we can find the desired service capacity, P_D:

$$P_D = s\kappa C^{\alpha\beta} A^{\alpha(1-\beta)} E^{(1-\alpha)} Q^{(1-\alpha)\beta} = sD$$

Then, taking current quality as given, we solve for the desired levels of assets A_D (and employees and capability) that minimize the cost of that capacity given the unit costs of factors of production from step 1. This results in:

$$A_D = B_D \alpha(1-\beta)/C_A$$

where desired budget, B_D, is:

$$B_D = \frac{sD}{\kappa \left(\frac{\alpha\beta}{C_C}\right)^{\alpha\beta} \left(\frac{\alpha(1-\beta)}{C_A}\right)^{\alpha(1-\beta)} \left(\frac{1-\alpha}{C_E}\right)^{(1-\alpha)} Q^{(1-\alpha)\beta}}$$

We could find the desired number of employees and labor similarly, from the same optimization problem. However, we note that assets typically move more slowly than employees and capabilities, so the goals for capabilities and labor could take current assets as given. We therefore define two more short-term problems, one to find desired capabilities given current levels of assets and another to find desired employee levels given the current levels of capabilities and assets.[2] We solve the analogous (but simpler) problems and find desired capability (C_D) and desired labor for customer service (E_{D_S}). These solutions are available as part of model equations. The desired labor for capability building (E_{D_C}) then accounts for the labor needed to maintain C_D and the labor to close the gap between the current capability level and the desired level over the capital adjustment time (t_C):

$$E_{D\_C} = \frac{\mathrm{Max}\left(0, \frac{C_D}{\mathrm{T}} + \frac{C_D - C}{t_C}\right)}{e_c Q}$$

Total desired labor, E_D, is the sum of desired labor for capability building and desired labor for customer service.

Step 3)

Assets erode with a time constant similar to that of capabilities (t_b) and are replenished and adjusted towards the desired level with a time constant t_C. Capability adjustment is achieved through employees who are allocated to capability building. Employee allocation first satisfies demand for customer service (E_{D_S}), then demand for capability building. If any labor remains (E_X), it is allocated between the two purposes based on task richness. With high task richness, the focus is on capability building and with low task richness, the focus is on customer service:

$$E_S = \mathrm{Min}\left(E, E_{D_S}\right) + E_X(1-\beta)$$
$$E_C = \mathrm{Max}(E - E_S, 0)$$
$$E_X = \mathrm{Max}(0, E - E_D)$$

[2] In equilibrium, the two approaches give identical results. They are also fairly similar dynamically, but the one we use leads to faster adjustments during transition and is behaviorally more realistic because it anchors the shorter-term factors on the current (rather than future optimal) values of factors with slower adjustment time.

In simulations of transitioning to IMax we deviate from the above employee allocation formulation, giving customer service and capability building equal priorities. This ensures capabilities are not starved when we move towards IMax starting with little capability.

Finally, the gap between labor and desired labor (G) is closed over the employee adjustment time (μ) through hiring (H) and through the faster of layoffs or voluntary turnover (U):

$$\frac{dE}{dt} = H - U$$

$$U = Max(-\frac{G}{\mu}, \frac{E}{\tau_V})$$

$$H = Max(0, U + \frac{G}{\mu})$$

$$G = E_D - E$$

Summary of model mechanisms and parameters- In Table S 1 we summarize key model mechanisms and parameters used in the base case. We also distinguish between policy levers and endogenous decisions formulated in the model.

Table S 1- Summary of model mechanisms, strategy choices, parameters, as well as parameter ranges explored for robustness

		Explanation	**Parametric Assumptions**
Mechanisms and Interdependences	**Direct**	Attracting quality employees requires higher compensation as well as screening and training costs	θ_C=0.7 [0-1.4]
		Increasing task richness requires labor for building and maintaining capabilities	e_c=0.1
		Task richness can enable recruiting of better employees	θ_T=0.1 [0-0.3]
		Faster employee adjustment makes jobs less attractive	θ_μ =0.07 [0-0.21]
		Quality employees increase service capacity (β) as these employees could be more productive, but also reduce shrink and spoilage and enhance customer experience and increase sales	δ_Q=0.1 [0-0.3] m_b=4 $/Customer [0-8]
		Capital intensiveness increases opportunities for quality employees building and maintaining capabilities, but reduces direct employee contribution to capacity	α=0.3 [0-0.9]
		The relative cost of assets over capabilities impacts economic tradeoffs	a_A=1 [0-2]
	Feedback	Motivated and skilled colleagues increase job attractiveness (Rewarding Environment- R1)	θ_Q=0.2 [0-0.6]
		On the job learning can enhances employee quality (B1)	λ=0.01 [0-0.03] ρ=1 [0-2]
		Job attractiveness impacts employee turnover, and thus its costs (R5)	ξ=1.5 [0-3]
		Service quality enhances customer loyalty (B2)*	γ_S=0 [0-0.6]
		Service quality impacts employee satisfaction (Personal Fulfillment-R3)*	θ_S=0 [0-0.6]
		Reduced turnover preserves quality employees and capabilities (R2 and R4)	ε_τ=0.2 [0-0.6]

Managerial Choices	Policy Levers	Compensation (including fixed and performance-based, as well as various benefits)	c
		Task richness (regulates the balance between assets and capabilities and moderates the contribution of employee quality to productivity)	β
		Employee adjustment time (use of part time positions, JIT scheduling, and rapid hiring and dismissal)	μ
	Endogenous Decisions	Desired Assets (the level of assets to acquire)	A_D
		Desired Employees (The full-time-equivalent number of employees to maintain)	E_D
		Capability Allocation (Fraction of employee time devoted to capability building)	f_s
		Initial training and Recruitment Costs (in $/Employee)	C_T

*These mechanisms are in the model but zeroed out in the base case analysis.

A 3-Analytical Solutions

Equilibrium performance various simplified versions of the model can be found analytically. Different simplifications can be made. We solve the most inclusive version of the model in which analytical expressions for steady-state profit are available and then provide more detailed analysis for the stylized version discussed in the paper. To this end, we remove only learning, training, and effect of task richness on job attractiveness from the model (no analytical solution exists without those simplifications) and use the following arguments to specify the equilibrium values for the state variables of the model:

- Baseline quality can be found using the equation for new employee quality because training and learning do not change quality in the simplified model:

$$Q_N = \left(\frac{c}{c_N}\right)^{\theta_c} Q^{\theta_Q} s^{\theta_S} \mu^{\theta_\mu}(1-\theta_T(1-\beta)) \Rightarrow Q_{Eq} = \left(\left(\frac{c}{c_N}\right)^{\theta_c} s^{\theta_S} \mu^{\theta_\mu}(1-\theta_T(1-\beta))\right)^{\frac{1}{1-\theta_Q}}$$

- Underlying demand can be found based on its base value and the effect of service quality on demand, keeping in mind that, in equilibrium, service quality equals desired service quality:

$$D_{U-Eq} = d_B s^{\gamma_S}$$

- Equilibrium capability, employees, and assets should be set to their desired levels—C_D, E_D, and A_D—discussed above. These are:

$$A_{D-Eq} = B_{D-Eq}\alpha(1-\beta)/C_A$$
$$C_{D-Eq} = B_{D-Eq}\alpha\beta/C_C$$
$$E_{D-Eq} = \frac{B_{D-Eq}(1-\alpha)}{C_E} + \frac{C_{D-Eq}}{e_C Q_{Eq}}$$

where desired budget in equilibrium, B_{D-Eq}, is:

$$B_{D-Eq} = \frac{s D_{U-Eq}}{\kappa\left(\frac{\alpha\beta}{C_C}\right)^{\alpha\beta}\left(\frac{\alpha(1-\beta)}{C_A}\right)^{\alpha(1-\beta)}\left(\frac{1-\alpha}{C_E}\right)^{(1-\alpha)} Q_{Eq}^{(1-\alpha)\beta}}$$

We can then replace these state variables in various model equations to calculate the equilibrium profit:

$$\pi_{Eq} = D_{U-Eq} m_b Q_{Eq}^{\delta_Q} - \left(c + \frac{c_h}{\tau_{V_b} Q_{Eq}^{\xi}}\right) E_{Eq} - \frac{c_N}{e_C t_b a_A} A_{Eq} - c_{Fixed}$$

In short, both equilibrium conditions and equilibrium profits can be calculated analytically after removing only the learning and training. However, the resulting expression for profit (as a function of model parameters) is quite complex and does not provide clear insights.

The summary of simplest version of the model

The profit function in the simplest version of the model can be calculated as:

$$\pi_{Eq} = d_b\left(m_b\left(\frac{c}{c_N}\right)^{\theta_c\delta_Q} - \mathrm{c}\frac{1}{\kappa Q^{\beta}}\right) - c_{Fixed}$$

This expression can also be written in terms of employee quality, Q, since $Q = \left(\frac{c}{c_N}\right)^{\theta_c}$ in the stylized model. That alternative expression yields the following (also discussed in the main text):

$$\pi_{Eq} = d_b\left(m_b Q^{\delta_Q} - \frac{c_N}{\kappa} Q^{\frac{1}{\theta_c}-\beta}\right) - c_{Fixed}$$

In this expression β only appears as exponent of Q in the denominator of employee cost contribution to profits. Therefore the optimal choice of β is a function of Q: if Q>1, then β=0 is preferred, otherwise β=1 is optimal.

These corner solutions for β, however, do not guarantee the emergence of two local peaks. Specifically, it may be that low (or high) Q values dominate so strongly that Q>1 (or Q<1) options are never even locally viable, regardless of β. For different Q values above and below 1 to be viable, a sufficient set of conditions include:

1) Assuming β=0 profit increases by reducing Q below 1. This will lead to a (local) peak at Q values below 1, where β=0. Formally: $\frac{d\pi}{dQ} < 0 \; at \; Q = 1 \; and \; \beta = 0$
2) Assuming β=1 profit increases by increasing Q above 1. This will lead to a local peak at Q values above 1, where β=1. Formally: $\frac{d\pi}{dQ} > 0 \; at \; Q = 1 \; and \; \beta = 1$

Writing down these two conditions and solving for the inequalities, we find the following sufficient conditions for having a bimodal landscape in our stylized model:

$$1 < \frac{c_N}{\theta_c \delta_Q m_b \kappa} < \frac{1}{1 - \theta_c}$$

For example, with our base case parameter values (c_N=2000; θ_C=0.7; δ_Q=0.1; m_b=4; κ=4000), both inequalities hold (1<1.79<3.33) and we do get a bimodal landscape. Note that the conditions above are sufficient, but not necessary, so there are other parameter settings that create bimodal landscapes but are not included in the condition above.

Complementarity in the stylized model

Formally, two elements of strategy are complements if the mixed partial derivative of performance with respect to those elements is positive. Here we show that in the stylized model task richness and employee quality are complements, i.e. $\frac{\partial^2 \pi_{Eq}}{\partial \mathrm{Q}\, \partial \beta} > 0$, for all feasible values of these two choices. Given that employee quality is only the function of compensation in this model, within the region of parameter space where employee quality is an increasing function of compensation, the result also holds for complementarity between task richness and compensation.

By taking mixed partial derivatives of profits with respect to task richness and employee quality we have:

$$\frac{\partial^2 \pi_{Eq}}{\partial \mathrm{Q}\, \partial \beta} = \mathrm{Q}^{\frac{1}{\theta_C} - \beta - 1} \left(1 + \left(\frac{1}{\theta_C} - \beta\right)\left(\frac{1}{\theta_C} - \beta - 1\right)\right)$$

Replacing $\varphi = \frac{1}{\theta_C} - \beta$ we get:

$$\frac{\partial^2 \pi_{Eq}}{\partial \mathrm{Q}\, \partial \beta} = \mathrm{Q}^{\frac{1}{\theta_C} - \beta - 1} (\varphi^2 - \varphi + 1)$$

This function is always positive for feasible Q (Q>0) since the second quadratic term, $(\varphi^2 - \varphi + 1)$, has a positive minimum at $\varphi = 0.5$ and thus is positive for any value of task richness and employee quality elasticity with respect to compensation (θ_C). Therefore Q and β are complements in their feasible region.

A 4-Performance landscape in higher dimensions

The main analysis used compensation and task richness (and employee adjustment time, μ, when considering stochastic demand) as the main managerial policy levers, calculating endogenously the other managerial decisions on desired assets, employees, employee allocation between capabilities and customer service, and training and recruitment costs. This treatment may raise the question about robustness of the findings on the number of local peaks. Specifically, one may argue that by incorporating efficient choices on four managerial decisions, we may be excluding many local peaks that are otherwise relevant to understanding the actual performance landscape. Here we examine this possibility by analyzing the expected performance of the firm in an augmented strategy space including all these four decisions as separate policy levers. Our focus is on identifying the number and location of local peaks. Absent visualization methods for a six-dimensional performance landscape and following previous research (Rivkin, 2000), we use multiple simulated random walkers that seek to find local peaks. Each is initialized from a random point on the six-dimensional strategy space defined based on feasible ranges for each decision (Table S 2). The walker then moves in random directions, taking small steps with random lengths not exceeding 1% of the length of any dimension. A step is accepted if it leads to performance improvements, otherwise the walker does not move and takes another step. This process is continued until the walker does not move for a very long time, indicating a local peak.

Table S 2-The range of managerial choices explored in the 6-dimensional strategy space as well as the two resulting peaks.

	Minimum	Maximum	IMax Peak	CMin Peak
c (compensation)	600	10000	4353	610
β (task richness)	0	1	1	0
A_D *(assets)*	0	3	0	0.9
E_D *(employees)*	0	40	6.4	13.9
C_T *(training and recruitment costs)*	0	3000	801	0
f_s *(fraction of employee time to capability building)*	0	1	0.3	0
Profit			50727	48065

We conducted this analysis using 60 walkers starting from random points on the strategy space and taking more than 10,000 steps each, where after each step they wait to realize the equilibrium performance outcome of the new position. Through this process all these walkers end up on one of two local peaks (ignoring tiny variations given continuous choices), with 49 landing on the IMax and 11 finding the CMin. Table S 2 also reports the values of 6 choices for the two peaks corresponding to CMin and IMax in this analysis. Both peaks are very similar to the ones found in the main analysis with the two-dimensional strategy space (training and recruitment costs prove rather unimportant, because they can be directly traded off against compensation; and the payoff landscape near IMax is rather flat on this dimension). Note that these solutions are not "corner" solutions in that many (but not all; e.g. task richness takes extreme values) choices take medium values.

No other local peak is found, suggesting that the landscape likely has the two local peaks that closely correspond to those identified in the main analysis. The relative number of walkers finding IMax vs. CMin provides a measure of relative size of basins of attraction for the two strategies in the six-dimensional strategy space. Consistent with the two-dimensional analysis, IMax has a larger basin of attraction in this setting as well.

A 5- Understanding the various impacts of feedback loops and model parameters

In light of the limited space in the main body of the paper here we provide additional analyses to help build a more nuanced understanding of the model. In moving from the simple analytical model to the more complex one we introduced a few feedback mechanisms, which we further augmented in this appendix. Therefore we focus our analysis in this section on demonstrating how those feedback effects operate to change both the equilibrium results and the dynamics of the model. The goal of this section is to both provide a more in depth understanding of the model mechanisms for interested readers, and to highlight the following three features of feedback mechanisms that make them important in our main analysis: 1) Feedback loops change the equilibrium costs/benefits of different strategies. 2) Loops introduce slow dynamics and 3) Feedback effects interact in nonlinear ways.

In doing so we conduct two analyses. First, we go deep into understanding the impact of one representative feedback loop, the R1-Rewarding Environment, using simulations that elaborate on both the dynamic and equilibrium results. Then we report more details on how various model parameters regulate the equilibrium results and dominant strategies.

A detailed example of effects of feedback loops

In our first analysis we use the scenarios discussed under temporal complexity section in the paper to elaborate on the different effects of feedback loops. Those effects could be summarized as 1) Direct impact on equilibrium tradeoffs; 2) Impact on dynamics; and 3) Interactions of loops that change both dynamics and equilibrium tradeoffs. To illustrate these basic effects, we focus on a case where the IMax is considerably better than CMin (by making the following parametric changes compared to the base run: λ=0.03, θ_Q=0.4, δ_Q=0.15). This is the scenario reported in the paper, in the temporal complexity section, and leads to a bimodal landscape with (47k, 64k) peaks for CMin and IMax. Similar to the main paper we focus on the dynamics of transition from CMin peak to IMax (by changing compensation from $1720/Month to $2830/Month and taking task richness from zero to one at time 5). Within this setting we analyze how the Rewarding Environment loop (R1) impacts the dynamics and equilibrium outcomes. Specifically we compare two scenarios, one with the above parameter settings (i.e. when the rewarding environment loop is active; we call that "R1 Active") and another where we put θ_Q to zero, keeping everything else the same (we call that "R1 Inactive"). Figure S 2 reports job attractiveness, Q_N, dynamics under these two scenarios (and a third discussed below), with the solid line representing R1 Active case, and the dotted line for R1 Inactive:

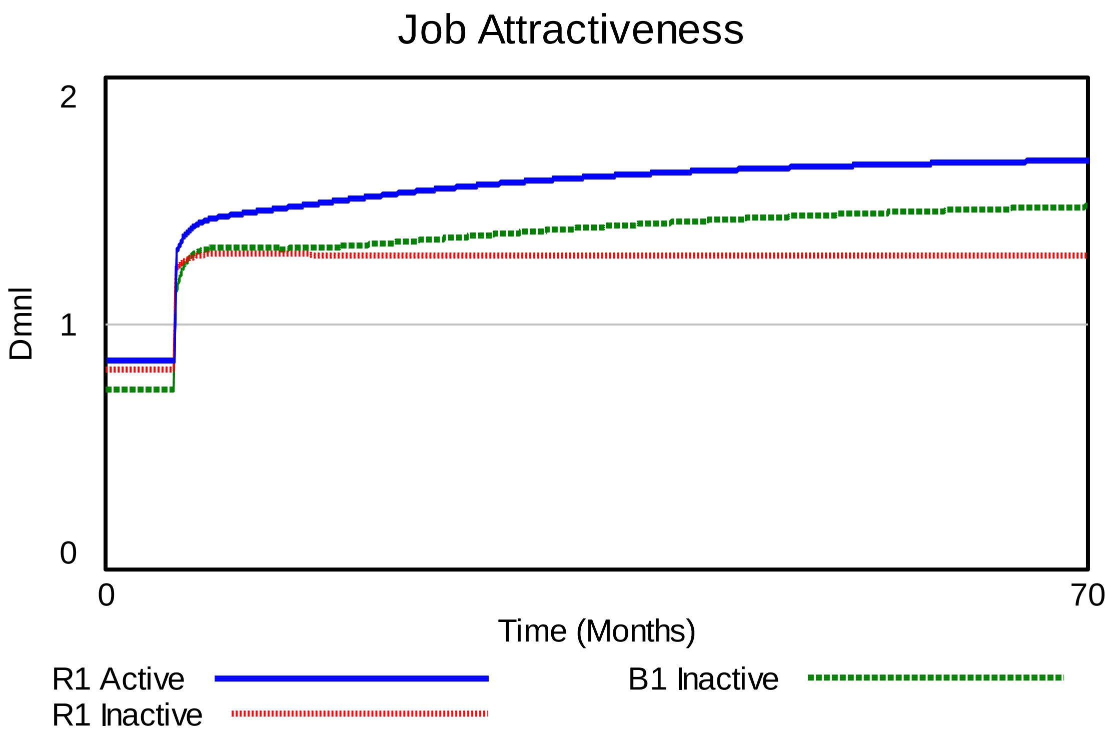


Figure S 2- Job attractiveness under three scenarios

Three effects stand out, and provide a good example of various ways in which the feedback loops contribute to relevant tradeoffs and dynamics. First, there is a gap between the two curves in equilibrium both under CMin (times 0 to 5) and IMax (towards the end of the simulation). Second, this gap is significantly larger under IMax vs. CMin. Third, when the rewarding environment loop is active, the gap grows in three distinct phases: a very quick initial rise, followed by a relatively fast increase (over a ~4 months period), followed by a slow gradual increase that takes years to settle. In contrast, the third, slow, phase does not appear in the absence of the rewarding environment loop. Let us tease out these effects starting with the initial gap between the two job attractiveness curves under CMin.

Here, job attractiveness is below one (during times 0-5), but not so low that it leads to high turnover rates. Therefore on the job learning (B1) loop has a notable impact on the accumulation of employee quality, so much so that average quality, Q, is above one. As a result the Rewarding Environment loop boosts Job Attractiveness in the R1 Active case compared to the R1 Inactive. Note that this result would have been reversed if we used the base case parameters (in which CMin entails employee qualities below one), or if the B1-Learning loop was inactive. Figure S 2 includes the latter scenario as well (B1 Inactive; dashed line), showing that the job attractiveness in the CMin region is actually lower for R1 active AND B1 inactive than it is in the case with only R1 inactive. The magnitude of the R1 effect, in comparing between R1 active and inactive, is rather small in the CMin region because employee quality is close to one, so the term Q^{δ} is not very consequential. This change in equilibrium due to R1 is a good example of the broader point: endogenous feedback loops can change the equilibrium points of the system, and their impact may vary depending on which region of strategy space we are operating in. Therefore these loops can strengthen one strategy vs. the other one.

To appreciate the second general point lets consider the dynamics of change in the strategy from CMin to IMax. At time 5 the transition to IMax is undertaken (changing both compensation and task richness) in a step function. Job attractiveness immediately jumps up as a result of those changes (the step increase in job attractiveness). Next, for a short while job attractiveness grows relatively fast as new employees, with higher quality, are hired to build capabilities. That adjustment is relatively fast, so its dynamics settle after a few months. The two scenarios are relatively similar across these two stages. The dynamic impact of R1 becomes evident considering the slow, longer-term increase in job attractiveness that follows after time ~10 months.

This slow increase phase is the result of the R1 loop's endogenous growth, and its interaction with the B1 (learning) and R2 (preserving knowledge) loops. Specifically, this growth is rather slow because the endogenous loop gradually shifts the goalpost for employee quality: as quality grows it increases the job attractiveness, which further enhances the employee quality further. The loop does not settle quickly because of the slow turnover in employees (after all they have good jobs!) which means their quality will not adjust quickly to the value indicated by job attractiveness. The slow, endogenous change in the state of the system is the second hallmark of feedback effects: they create dynamics that gradually shift the state of the system long after exogenous changes have ceased.

We may also note that the high employee quality in the IMax region further reduces the turnover rate, extending the delay in the adjustment of employee quality. This is one interaction of R1 and R2 (preserving knowledge) that changes the delays depending on which region of strategy space they are active in. Another noteworthy interaction includes the impact of B1. Comparing the B1 Inactive and R1 Active scenarios in Figure S 2 we note that when both loops are active, the quality grows more rapidly between the months 10 and 25 (solid blue line). No such growth is present in the absence of B1 (dashed green line). The reason is that on the job learning (B1) plays an important role in enhancing average employee quality when new employees are recruited for building organizational capabilities. On the other hand, the gradual increase in quality due to learning (B1) also strengthens the impact of R1, thus further increasing the job attractiveness. B1 acts as a trigger that activates R1 and shifts the system's dynamics. So overall the gap between R1 Inactive and R1 Active grows over time, and also between IMax and CMin regions as a result of the interactions between R1 and B1. This provides an example for a third general point: that feedback loops interact both in determining the dynamics and in determining the equilibrium effects of various loops.

This example demonstrates three relevant features of feedback effects: they change the equilibrium costs/benefits of different strategies, they introduce slow dynamics in moving towards those equilibrium outcomes, and their effects interact in nonlinear ways, potentially building on each other in some regions and cancelling out in others. In the next set of analyses we dive deeper into understanding the effect of each model parameter as it influences the equilibrium tradeoffs among different feedback loops and mechanisms.

Impact of individual parameters on competing strategies

In this analysis we changed parameters listed in Table S 1 within the ranges specified there, keeping other model parameters unchanged. For each value of the parameter, we conduct two optimizations, finding the profit-maximizing (in equilibrium) compensation (*c*) under task richness values of one and zero. We limit our search to these two extremes because, in the vast majority of cases, the best configurations for the IMax and CMin strategies fall on these values and this choice simplifies the visualization of results. In Figure S 3, we report the compensation and desired service quality for the dominant strategy (the result of optimization that offers the higher profit of the two; left Y-axis). For clarity, we highlight regions in which Task Richness of 0 (vs. 1) dominates. We also report the difference in profits under the two strategies on the same graph (right Y-axis). Here, we discuss in detail four exemplars (Panels A-D) that best characterize the impact of direct factors and feedback loops on equilibrium costs and benefits.

Dominant strategy, in this analysis, is about equilibrium results. Therefore the sensitivity of the dominant strategy to various parameter values is best understood in light of its costs and benefits. For example, in Panel A, reducing the effect of the work environment on job attractiveness (θ_Q) weakens the Rewarding Environment (R1) and Engaged People (R4) loops. By increasing the costs of quality and reducing its benefits, there is a threshold below which investment in quality employees can no longer be optimal, even with full task richness. Thus a profit-maximizing firm would switch to task designs with lower engagement and complexity, which allow it to manage well with low-quality and low-cost employees (assuming good execution). Factors that weaken θ_Q include job designs that isolate service workers and reduce interaction; for example, by narrowing their tasks or assigning unpredictable schedules. On the other hand, strengthening this relationship—and the corresponding loops—calls, at the transition threshold, for a significant increase in compensation (dashed line) to enable attracting quality employees in combination with these feedback mechanisms. However, if R1 is strong enough, there is no need to rely heavily on compensation to make the jobs more attractive, because quality employees join due to the ‘Rewarding Environment’ effect, a compensating differential effect. Note another relevant feedback that we do not model explicitly: an increase in task richness, by requiring more complex processes and social and human interactions, is likely to increase θ_Q and thus to increase the reinforcing loops that support the IMax strategy. In contrast, low task richness strengthens the cost-minimization equilibrium by cutting θ_Q.

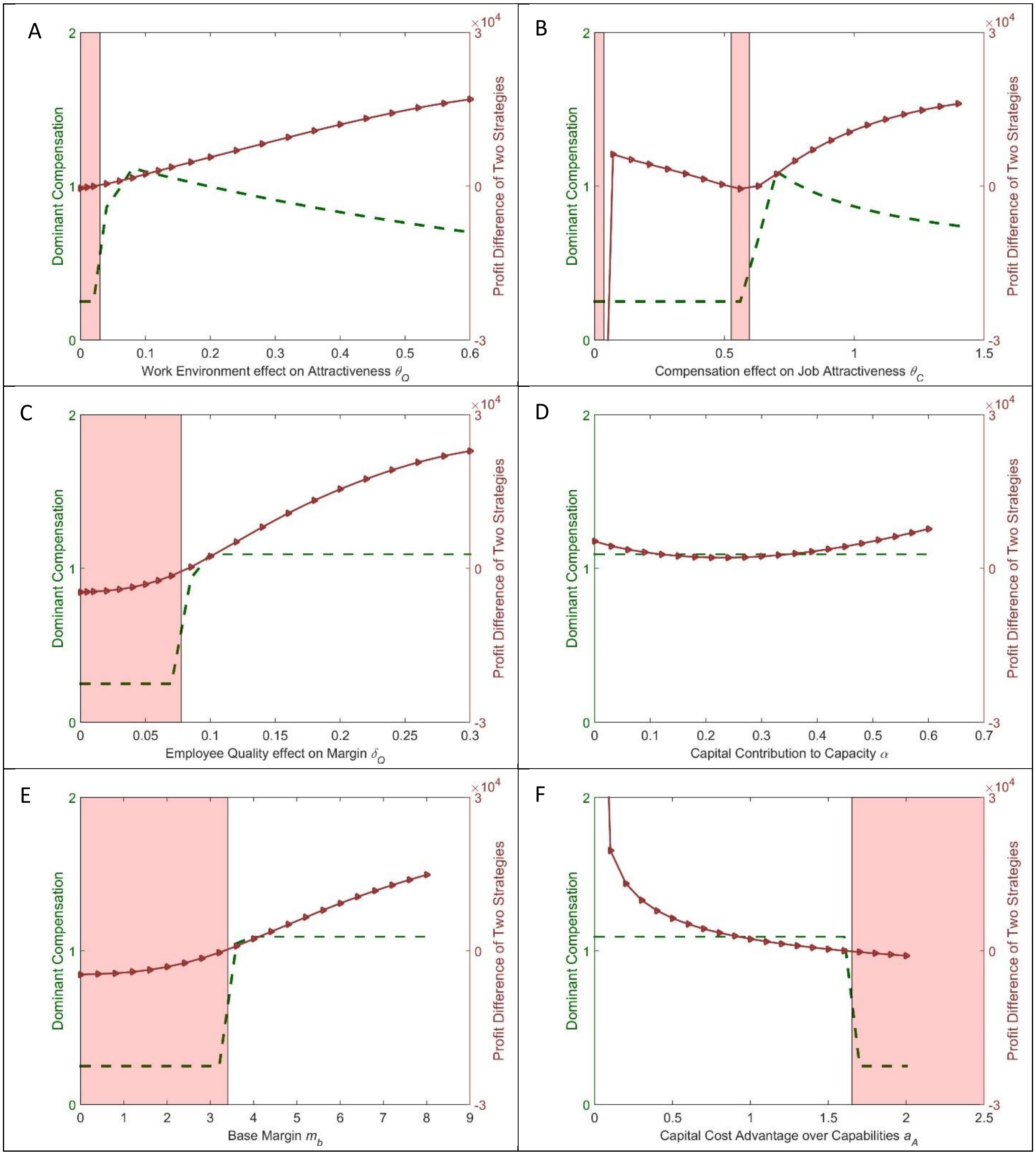
The effect of compensation on job attractiveness (θ_c) is more subtle. High task richness dominates at both low *and* high levels of θ_c (Panel B). When potential employees are not sensitive to compensation, the firm can recruit relatively high-quality employees and build a rewarding environment at low cost. This strategy leverages other features of the IMax peak (high task richness, high service quality, rewarding environment), but is distinct in its low compensation. Thus, it is not a stereotypical example of ‘IMax,’ but it may be close to the model followed by many nonprofits and voluntary organizations (albeit not in mass market services), which we called ‘volunteer-based’. On the other end of the spectrum, a high sensitivity of labor to compensation means that low compensation would significantly reduce the quality of candidates, making it cheaper to kick-start the feedback mechanisms by paying more and attracting quality people. For example, significant productivity heterogeneity in some technical jobs, such as software engineering, or in tight labor markets can promote the IMax strategy through higher θ_c. However, in the middle range of θ_c, the costs of hiring quality employees may overwhelm the benefits and promote the combination of low task richness and low compensation[3]. The exact width of this range depends on how other features of the industry promote IMax. In fact, if the feedback effects are powerful regardless of θ_c, then high task richness may dominate throughout.

The effect of employee quality on margin (δ_Q) influences profitability directly and exemplifies the direct benefits of employee quality. The stronger this effect, the higher the value of quality employees and thus the higher the likelihood of adopting the IMax strategy (Panel C). In our setting, the transition is achieved by significantly increasing compensation to achieve maximum quality (q_{Max}). For example, quality employees have a strong effect on sales and margins in high fashion, thus strengthening the preference for the IMax strategy in that sector. Note that optimal compensation is kept at that maximum level because, contrary to the analysis on θ_C, no feedback effects are activated by δ_Q to enhance employee quality using nonmonetary factors.

Various features of technology and industry also bear on the dominant strategy. When capital plays a larger role in production, feedback loops' benefits are more pronounced. Those benefits are seen in higher productivity of quality employees in building capabilities and longer capability life under low turnover. Thus, increasing capital's share in capacity may actually promote IMax, as long as capital can be built internally in the form of capabilities (Panel D). For example, in many capital-intensive industries, the importance of physical asset maintenance and process improvement promotes IMax, despite the relatively lower share of labor in production.

Overall, mechanisms and design choices moderate the dominant strategy according to their effects on the costs and benefits of employee quality. These effects, especially the feedback ones, sometimes compensate for each other, leading to sharp nonlinearities in optimal policies. For example, switching to an IMax equilibrium may require a significant increase in compensation; but once high employee quality has been achieved, financial compensation may lose its power to promote further profitability. Instead, work environment and service quality can become viable drivers of employee quality. Finding the right balance in this setting is complex. For example, enhancing task richness makes feedback benefits of employee quality possible by strengthening R1-5. Thus, both strategies become coherent internally, although distant in the strategy space. Managers who follow a labor-cost-minimization approach may find it unimaginable that the IMax strategy can be cost-effective in their industry. They perceive limited returns on quality, because those returns are explicitly designed out of their current business model by the focus on simplified and routine tasks and the avoidance of more complex organizational processes. Extrapolating from this experience, they see the IMax strategy as a failing proposition inconsistent with the basic economics of the industry as they know it.

[3] Panel B also shows CMin to dominate when θ_C=0; This is because neither strategy can offer positive profits due to the fact that optimum training with marginal returns equal to that of minimum compensation ($1000) is very expensive, and more so for the IMax strategy. This extreme mechanism is not realistic or relevant to our main results.


A
B
C
D
E
F
Dominant Compensation
Profit Difference of Two Strategies
$\times 10^4$
Work Environment effect on Attractiveness θ_O
Compensation effect on Job Attractiveness θ_C
Employee Quality effect on Margin δ_Q
Capital Contribution to Capacity α
Base Margin m_b
Capital Cost Advantage over Capabilities a_A

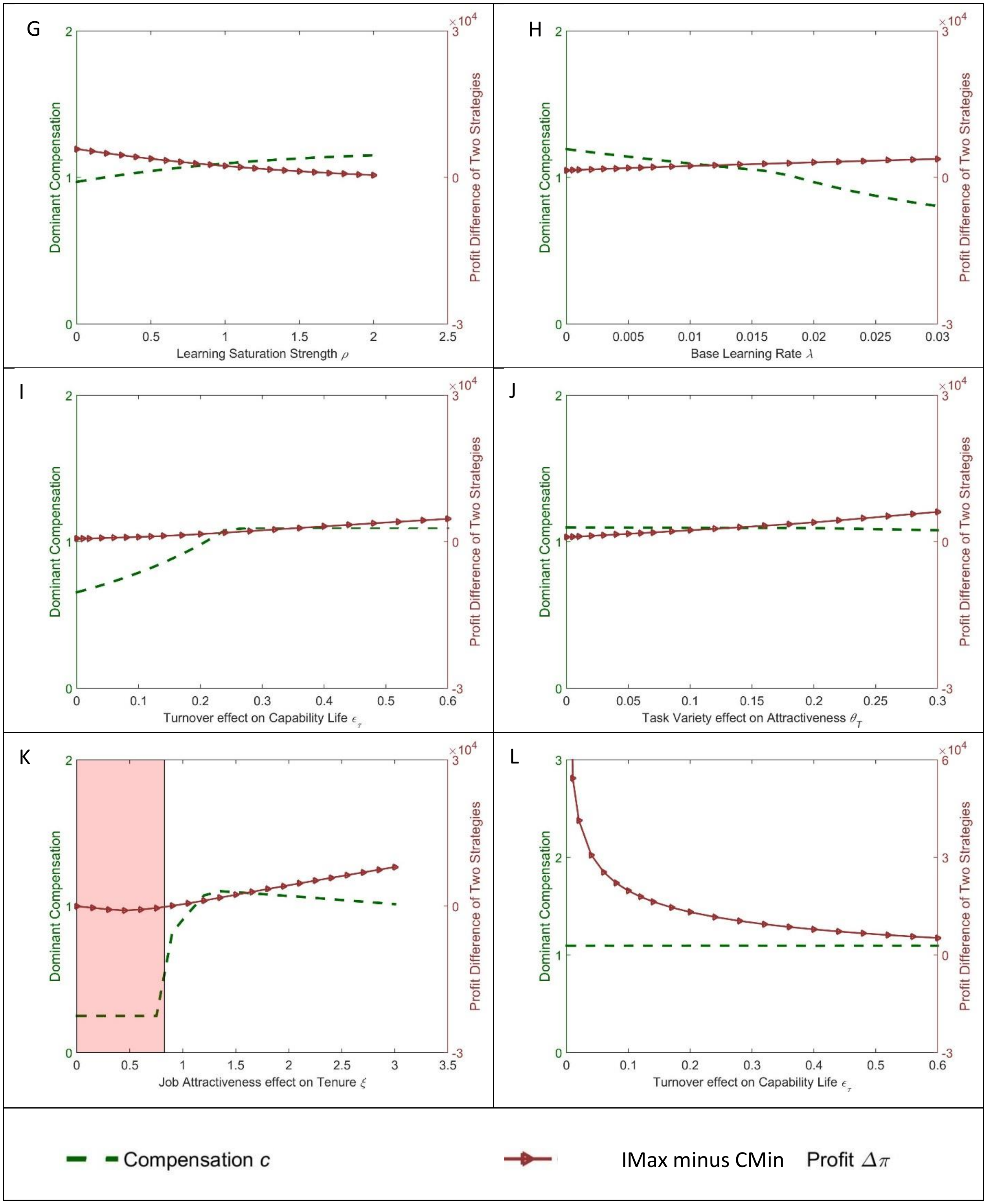


Figure S 3-Full sensitivity analysis of dominant strategy at different parameter values. Each graph reports the profit maximizing compensation (in \$4000/month multiples; dashed line; left Y-axis) and difference in profits following the profit maximizing policy with task richness of β=1 minus the counterpart profit under β=0 (triangular marker; right Y-axis). Regions where CMin dominates are highlighted in pink. For each value of parameters on the X-axes two optimizations are conducted, finding profit maximizing compensation and service quality with task richness values of 0 and 1. The compensation values for the strategy with higher overall profits are graphed only.

A 6- Sensitivity Analysis and Boundary Conditions

The analyses reported in the paper established the existence of two coherent strategies in managing service operations: the IMax strategy and CMin. In this section, we explore the conditions under which each strategy dominates. Based on the results in the previous section we identify the five most important model parameters and conduct a multi-dimensional sensitivity analysis on those five parameters. By generating the landscape topology maps for more distant points in the parameters space, we can assess (a) the conditions under which the two strategies persist, (b) when a single dominant strategy emerges, and (c) the conditions under which each peak dominates.

Overview: Our baseline model parameters may be different from those of many actual service operations. Thus, besides analyzing sensitivity to individual mechanisms, we need to explore the parameter space for conditions leading to the separation of the two peaks in the strategy space and the dominance of each peak. We do so by conducting a multivariate sensitivity analysis, changing five main model parameters and, in each case, inspecting the strategy-payoff contour plots (similar to those in Figure 2 of the main paper) to identify the number and location of peaks in the strategy space. By changing the important parameters at the same time, we explore the more distant market and industry settings. We choose the five parameters to include the more important effects in changing the costs and benefits. These include (a) the effect of employee quality on margin (δ_Q), a direct contributor to the benefits of quality; (b) the effect of compensation on job attractiveness (θ_c), which moderates the direct costs of quality; (c) the contribution of capital to capacity (α), a moderator of the feedback benefits of quality; (d) the effect of work environment on job attractiveness (θ_Q), which affects the costs of quality through feedback loops; and (e) the effect of job attractiveness on tenure (ξ), relevant to multiple feedback loops and to the direct benefits of quality. We draw each parameter independently from a uniform distribution within a wide range (reported in Table S 3 below), analyzing 1000 scenarios, which, with 99 strategy settings in each scenario (11 task richness levels * 9 compensation levels between 1000 and 5000 $/month), leads to 99,000 simulations. We use logistic regressions (reported in Table S 5 below) to better understand the features of this multidimensional parameter space. Figure S 4 summarizes the results qualitatively, showing the most common behavior in various combinations of direct employee-quality costs (θ_C on the Y-axis) and a linear composite of four other factors that summarizes the benefits of employee quality (X-axis; see figure caption for details).

One interesting finding from the previous section that is reinforced here is a nonlinearity in optimum task richness as a function of compensation effect on employee quality (θ_c). Where employees are insensitive to compensation (very low θ_C) organizations can retain quality employees using non-monetary levers, maximize task richness, and organize around the benefits of employee involvement without incurring the compensation costs. This is a qualitatively distinct peak with low compensation and high task richness, one that we had not anticipated. While not realistic in mass market services (where employees are sensitive to compensation), this peak maps well into non-profit and voluntary organizations, so we label it 'volunteer-based'. Medium levels of θ_c are more likely to promote the CMin and low task richness, because building employee quality is not cheap anymore, but quality (and thus output) returns on compensation remain modest. Finally, at high levels of θ_c the IMax peak becomes dominant again and compensation's strong impact on employee quality makes it worthwhile to pay for getting the best available talent. Despite the potential existence of the volunteer-based peak, no single landscape contained more than two local peaks from these three possible alternatives (or others).

We find that the coexistence of two local peaks is a fairly general outcome which persists under many possible industry, technology, and market settings captured in our different parameter values; it occurred in 96.1 percent of our analyzed scenarios. These multi-peak conditions are designated in Figure S 4 with the suffix 'M' (in contrast to scenarios dominated by a single peak, designated with the suffix 'S'). IMax (HH: high compensation, high task richness) dominates in 74 percent of the scenarios, followed by volunteer based (LH: low compensation, high task richness) at 22 percent and CMin (LL: low compensation, low task richness) at 4 percent.

HH can be promoted by activating causal pathways that reduce the costs or increase the benefits of employee quality (right-hand side of Figure S 4). Most dominant HH peaks are a result of (a) reductions in the direct cost of employee quality (high θ_C), (b) high direct benefits of quality (high δ_Q), (c) high benefits from leveraging quality employees through capability building (high α), or (d) increases in the costs of turnover for poor jobs (high ξ). On the other hand, an LH peak becomes dominant when employees are insensitive to financial incentives (very low θ_C; lower part of the graph) and employee quality has only marginal benefits. In such settings, the dominant strategy still relies on increasing task richness and benefiting from medium- to high-quality employees. Yet those employees are retained through an attractive work environment, a rewarding experience in satisfying the customers, and engaging tasks, rather than through compensation. When labor-cost minimization dominates, employee quality should be somewhat sensitive to compensation (medium θ_C) and the main pathways to the benefits of employee quality should be very weak; for example, through limited impact of capital (low α), lack of feedback mechanisms to save on employee costs (low θ_Q), limited direct or feedback benefits of quality (low δ_Q and α), and low turnover costs for unattractive jobs (low ξ).

Two local peaks coexist when combinations of effects do not lead to a significant advantage for any of the three competing job designs (HH, LH, and LL). Direct benefits of employee quality—for example, through their effect on margin (δ_Q)—are salient both in our model and in the real world. For example, the productivity variance among software developers, sales personnel, and financial analysts with different quality levels may well justify high task richness and compensation in these industries. Nevertheless, in the absence of those direct benefits, HH or LH can still be the sole peaks if endogenous cost-reduction mechanisms are in place (high θ_Q), if capabilities are important (high α), and/or if the turnover costs of poor working conditions are significant (high ξ). On the other hand, under specific conditions, labor-cost minimization is the only viable strategy because (a) task richness is limited to low values (b) capital is not important (or only assets are cost-effective), or (c) turnover costs due to poor jobs are limited *and* both direct and feedback-based benefits of employee quality are insignificant. Jobs in highway tollbooths and in parking lots, for example, given their minimum opportunities for employee contribution, may offer no viable strategy other than labor-cost minimization.

Sensitivity analysis highlights another effect. Non-monetary contributors to job attractiveness can act both as complements and substitutes for compensation. At lower levels they complement each other to promote the IMax peak over CMin, so small increases in one factor can significantly boost optimum compensation. However, once the IMax peak dominates, additional intrinsic benefits (e.g. stronger rewarding environment loop) *reduce* optimal compensation, following a logic of compensating differentials (Smith 1979).

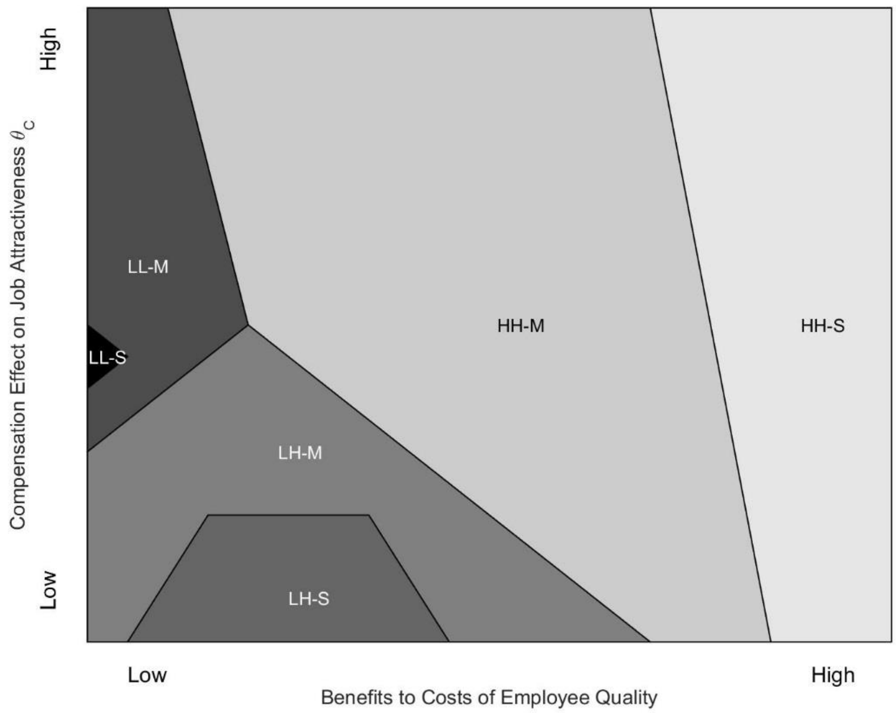


Figure S 4- Qualitative overview of the dominant peaks in the paraemter space identified based on high/low for compensation and task richness levels, and multiple (-M) or single (-S) peak. So LH-M means a combination of low compensation and high task richness dominates in the presence of at least one other local peak. The X-axis is a composite of how strong the benefits of employee quality are and how much of the cost of raising quality can be saved through feedback mechanisms. We use a weighted sum of δ_Q, α, ξ, and θ_Q , ($4\delta_Q+5\alpha+0.5\xi+0.6\theta_Q$ leads to results that are visually similar to the graph above, though borderlines are not as sharp) to quantify this axis. The Y-axis reflects θ_C. The graph is qualitative and, due to nonlinear interactions, one cannot account for every scenario in a two-dimensional graph.

Implementation Details: For this analysis, we change the values of five key model parameters using a uniform distribution changing each parameter between low and high values reported in Table S 3. For each of the 1000 random points in this parameter space, the full strategy space is mapped using values of task richness between zero and one and compensation between \$1000 and \$5000 per month with increments of \$500/month. For each scenario, we record the number of peaks and their locations on the four possible quadrants (determined based on compensation and task richness thresholds of \$2000/month and 0.5, respectively). We label these quadrants HH (for high compensation and high task richness), HL, LH, and LL. We then record which peak dominates the results, so a scenario coded with a dominant peak of LH has its profit-maximizing peak at low compensation and high task richness. We call a scenario multiple-peaked if there are peaks in at least two quadrants.

	Parameter (labels)	***Low***	***Base***	***High***
α	Capital contribution to capacity	0.1	0.3	0.8
δ_Q	Effect of employee quality on margin	0	0.1	0.3
θ_c	Effect of compensation on job attractiveness	0.1	0.7	1.4
θ_Q	Effect of work environment on job attractiveness	0	0.2	0.5

ξ	Effect of job attractiveness on tenure	0.2	1.5	4

Table S 3-Full factorial sensitivity analysis parameters

Table S 4 reports the number of scenarios with at least one peak in each quadrant and the number with dominant peak coming from each quadrant.

	HH	HL	LH	LL
# scenarios with at least one peak	753	429	248	532
# of scenarios with dominant peak	744	0	217	39

Table S 4-Number of different types of peak and their dominance in full factorial sensitivity analysis

Two questions drive our analysis in this section: (1) Which peak dominates? (2) When would we have more than one peak in the strategy space? We used logistic regressions on the data from the above multidimensional sensitivity analysis to address these questions and summarized the results above and in the paper. Here we describe the details of the analysis. Simple logistic regressions explain much of the variation in the results. The final regressions, shown in Table S 5, summarize how different parameter combinations lead to the dominance of one or another peak and when they promote multiple peaks. Specifically, θ_C (sensitivity of employee quality to compensation) and δ_Q (sensitivity of margin to employee quality) are the most significant drivers of dominant peaks, followed by θ_Q (sensitivity of employee quality to work environment), α (importance of capital in production function), and ζ (impact of job attractiveness on turnover).

	HH	*LH*	*LL*	*Multiple peaks*
Intercept	-54.16 (7.39)	28.2 (3.67)	1.66 (1.75)	8.86 (1.88)
θ_C	83.02 (11.63)	-38.89 (4.81)	21.61 (5.42)	-7.52 (1.35)
α	6.18 (1.47)	2.39 (1.2)	-8.64 (1.68)	51.95 (9.83)
θ_Q	26.97 (4.01)	-17.53 (2.65)	-6.77 (1.82)	-9.72 (2.73)
δ_Q	64.76 (9.12)	-27.45 (4.26)	-68.48 (11.28)	-37.41 (6.83)
ξ	3.69 (0.54)	-2.85 (0.43)	-0.79 (0.25)	
θ_C^2	-37.58 (5.66)		-16.97 (4.13)	
AUC	0.997	0.996	0.983	0.993

Table S 5-Logistic regression results for predictors of dominant peak and of the existence of multiple peaks. All models and parameters are statistically significant. AUC reports area under the Receive Operating Characteristic (ROC) curve and is a measure of goodness of fit for the model (changing between 0.5 and 1; values close to 1 suggest better models).

References

Rahmandad, H. 2012. Impact of Growth Opportunities and Competition on Firm-Level Capability Development Trade-offs. *Organization Science* **23**(1) 138-154.

Rahmandad, H., R. Henderson, N.P. Repenning. 2018. Making the Numbers? "Short Termism" and the Puzzle of Only Occasional Disaster. *Management Science* **64**(3) 1328-1347.
Smith, R.S. 1979. Compensating Wage Differentials and Public-Policy - Review. *Industrial & Labor Relations Review* **32**(3) 339-352.