Paper to be presented at the

35th DRUID Celebration Conference 2013, Barcelona, Spain, June 17-19

Taking time to do it right: The impact of time-compressing experience accumulation on organizational quality outcomes

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Abstract

Organizations develop new capabilities through ?learning by doing?. As firms accumulate more experience with production, their productivity increases at a decreasing rate. However, prior work has not examined how speed in experience accumulation (as opposed to the volume of accumulated experience) impacts the organizations? learning curve. We analyze this question using data from fertility clinics in the UK. We show that faster experience accumulation is associated with lower birth rates. We also show that the impact of time compression is exacerbated for clinics that mainly treat complex cases and is mitigated for clinics that employ an integrator to coordinate across the different specialist functions involved in the treatment process. Our results empirically show one mechanism ? shallower learning curves ? that gives rise to time compression diseconomies.

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ABSTRACT

Organizations develop new capabilities through “learning by doing”. As firms accumulate more experience with production, their productivity increases at a decreasing rate. However, prior work has not examined how speed in experience accumulation (as opposed to the volume of accumulated experience) impacts the organizations’ learning curve. We analyze this question using data from fertility clinics in the UK. We show that faster experience accumulation is associated with lower birth rates. We also show that the impact of time compression is exacerbated for clinics that mainly treat complex cases and is mitigated for clinics that employ an integrator to coordinate across the different specialist functions involved in the treatment process. Our results empirically show one mechanism – shallower learning curves – that gives rise to time compression diseconomies. (125 words)

Key Words: learning curve, time compression diseconomies, capability accumulation processes, task complexity, organizational adaptation.

INTRODUCTION

One of the most important issues in strategy research is to understand the factors that influence how firms develop capabilities (Teece, 2007). We define a capability as the firm's ability to generally reliably produce a desired outcome via intentional action, such as make cars or cure diseases (Dosi, Nelson and Winter, 2000)[1]. Learning by doing is one of the most important means available for a firm to develop capabilities. As individuals and organizations gain more experience with a production activity, the cost of production typically decreases at a decreasing rate. This phenomenon has been variously called learning curve, progress curve, or experience curve (Argote, 1999). However, prior research has not examined how the rate of experience accumulation impacts capability development in firms. We examine this question using data from fertility clinics in the UK. We show that firms that accumulate experience much faster than mean are likely to have lower success rates.

We use a stylized example to make our research question more concrete. Consider two fertility clinics, A and B that have just started. Suppose that clinic A on average treats one patient in 20 minutes but clinic B treats one patient in 30 minutes. If each clinic works for 8 hours a day, 250 days in a year, at the end of the year, clinic A has treated (24*250) 6000 patients, but clinic B has treated (16*250) 4000 patients. Ceteris paribus, is clinic A or clinic B likely to have better patient outcomes at the end of one year? This is an interesting question to ask because at the end of one year, clinic A has treated more patients, and therefore has marched further down the experience curve, but it has done so faster than clinic B, and therefore, may also be subject to time compression diseconomies. Prior work, to our knowledge has not considered how the rate of experience accumulation (as opposed to the volume of accumulated experience) impacts learning curves.

[1] For a discussion of the various existing constructs (capabilities vs. skills vs. competence vs. routines, etc.), we refer to Dosi et al. (2000) who clarify terminologies and discuss related issues in the first chapter of their book.

Dierickx and Cool (1989) introduced the concept of time compression diseconomies (TCD) as: "Conceptually, time compression diseconomies and the notion of 'strictly convex adjustment costs' in the theory of capital investment to which they are related, express the same fundamental mechanism: the 'law of diminishing returns' when one input viz. time is held constant." (p1507)[2]. They were interested in the consequences of TCD: it is one of the reasons for immobility of resources and therefore contributes to sustained competitive advantage. Subsequent scholarship, both modeling (Pacheco-de-Almeida & Zemsky, 2003; Pacheco-de-Almeida & Zemsky, 2007; Pacheco-de-Almeida, 2010) and empirical (Knott et al., 2003; Pacheco-de-Almeida et al., 2008), similarly concentrates on the consequences of TCD for competitive advantage, specifically for the problem of investment under uncertainty. For example, Pacheco de Almeida, Hawk and Yeung (2008) show that firms with the capability to accelerate plant building in the petrochemical industry compared to industry average enjoy higher Tobin's q, though they do not show what constitute these capabilities or how they are acquired.

Other work has concentrated on the impact of time compression operationally – from a project management view-point. Pacheco-de-Almeida et al., (2008) show that the faster a petrochemical plant is built, the higher its cost. Reduced time implies tighter coordination needs, parallel rather than sequential development and lower constraints on error. These likely require higher slack resources leading to escalating costs (Carroll, Burton and Levitt, 2007). However, these studies are not about the capability accumulation processes.

Prior empirical work has shown that TCD exists. Vermeulen and Barkema (2002) show that time compression in foreign expansion has a negative impact on ROA of Dutch multinationals; Knott et al (2003) also show evidence for time compression diseconomies in building R&D knowledge stocks in the pharmaceutical industry. However, now, twenty years

[2] We should note that Dierickx and Cool (1989) and most subsequent work applied the concept of TCD to accumulating resources. We are applying the concept to developing a capability.

after the original ideas were published, prior work has not yet examined the micro-level factors that give rise to TCD; what is the mechanism by which time compression leads to diseconomies in the capability development process? Therefore we cannot answer questions such as under what conditions the effect of time compression is mitigated and under what conditions it is exacerbated.

We take a learning curve approach to this question. Learning by doing is one of the fundamental means of developing a capability (Arrow, 1962; Nelson and Winter, 1982; Argote, 1999). However, organizations can accumulate the same level of cumulative experience, the typical measure of learning by doing, in different time frames, such as in the example presented above. We argue that compressing experience accumulation negatively impacts learning, and therefore hampers capability development in firms. We equate speed of experience accumulation with time compression, and estimate its impact on quality of organizational outcomes after controlling for the firm's cumulative experience. We aim to show that faster firms have shallower learning curves.

We use data from fertility clinics in the UK to understand these questions. We find that significant time compression diseconomies exist in fertility clinics. When cumulative experience increases by one standard deviation, increasing accumulation time by one standard deviation increases the number of live birth events by 122%. We show that these effects are exacerbated in clinics that handle more complex cases, showing that time compression has a more deleterious impact when the organization handles difficult problems. We also show that the effect of time compression is mitigated when the clinic employs a coordinator whose role involves coordinating the work of different specialists involved in the fertility treatment process. This shows that coordination ability allows firms to benefit more from their experience. These results indicate that time compression diseconomies are partly caused by reduced learning in the organization and partly a consequence of coordination problems.

These results contribute to our understanding of the causes that underlie one of the fundamental concepts in strategy. By showing that time compression in experience accumulation negatively impacts learning curves, we have identified one mechanism that leads to time compression diseconomies. Understanding the factors that explain capability accumulation processes such as TCD helps us understand the micro-foundations of capability development, which several recent papers have suggested is important for understanding organizational adaptation (Teece, 2007; Felin et al, 2012; Winter, 2012).

We also contribute to the learning curve literature by shedding light on contextual factors that impact outcomes to organizational experience. Recent research on learning curves has moved away from empirically documenting their existence in different settings and towards understanding the factors that moderate the extent of learning by doing in firms (Stan and Vermeulen, 2012; Wiersma, 2007; Haunschild and Sullivan, 2002; Pisano et al, 2001; Huckman and Pisano, 2006; Reagans, Argote and Brooks, 2005). We add to this literature by showing that the time scale in which cumulative experience was achieved, significantly impacts organizational outcomes. In addition we discuss factors that amplify or diminish the importance of time compression on learning.

THEORY AND HYPOTHESIS

Effect of time compression on learning: Learning curves at the organizational level are typically a composite function of several micro-processes including individual learning, improvements in production technology and improved product and process design (Adler and Clark, 1991; Dutton and Thomas, 1984; Argote, 1999). We expect time compression to impact each of these components of an organization's learning curve.

Individual learning is one of the most important components of the learning curve (Argote et al, 2005; Boh et al, 2009Learning by doing improves outcomes by two means: enhancing motor skills and dexterity in the tasks and by enabling individuals to develop more accurate and complete mental models of the tasks that leads to more effective problem solving (Clancey, 1987; White and Fredericksen, 1986).

In addition, studies on how individuals learn suggest that passage of time, not just accumulation of experience, is important for developing expertise. Ericsson and Lehmann (1996), from a study of experts in various fields, suggest that developing expertise with exceptional performance typically takes several years, and requires extensive deliberate practice, usually on a daily basis. Studies of exceptional performance find that both the most talented and the most ambitious (in terms of training hours) individuals are bound to the rule that expertise development takes time (Charness et al., 1995; Schulz et al., 1994). Studies in developing motor skill tasks have also found that passage of time (Shadmehr & Holcomb, 1997) and sleep (Walker & Stickgold, 2006) are essential to learning, since they help with memory encoding, consolidation and associated changes in the brain structure.

Time compression in experience accumulation is likely to lead to inferior individual outcomes for two reasons. First, individuals with less developed mental models are producing more output, which are likely to have a higher proportion of errors. The studies on "passage of time"[3] suggest that mental models are likely to be less developed in individuals who gained their experience in shorter time period than those with the same experience acquired over a longer period.

Second, it is intuitive that stress hampers learning. Many studies have shown that learning, especially motor skill learning, results in changes in the physical brain structure

[3] In time compression, we ask how performance differs if we allocate 1 day for a task instead of 2 days. In passage of time, the question is whether 10 hours in one day has the same performance effects as 5 hours over 2 days (or whether a semester long regular course is equivalent to a week-long crash course, both involving 30 contact hours). There is little research on the latter question, but it is important to understand, since individual learning over a longer period of time is required for capability development.

such as dendritic growth. Subjecting the learner to stress hampers such neural changes (Kolb & Whishaw, 1998). Other studies, in the acquisition of motor skills, have shown that adequate time between trials is helpful in mastering a skill (Shadmehr and Holcomb, 1997). Therefore, time compression to the extent that it leads to high workloads, and contributes to stress and mental fatigue in the individual is likely to severely handicap individual learning. For example, consider the case of a physician who sees 20 patients a day instead of 10 patients. Though the former physician is accumulating more experience, she is also more likely subject to stress, feel time pressure, and suffer from mental fatigue, which in combination are likely to lead to poor outcomes for patients. In the healthcare setting, Kc and Terwiesch (2009) show that an increase in workload in hospitals leads to deteriorating service quality and increased mortality.

Apart from individual learning, time compression in experience accumulation is also likely to have negative effects on the other two components of the learning curve – improvements in production technology and improved process and product design. If the firm has a high throughput rate, it processes more input with older designs and technology, potentially leading to inferior outputs on the aggregate. Also, when individuals are working under heavy workload conditions, they may have less time to think about process improvements or time to meet and share lessons learned and generate best practices.

Prior work has argued that organizations learn in a process of experimentation, communication and knowledge codification (Gibson and Vermeulen, 2003; Prencipe and Tell, 2001). When experience accumulation occurs under conditions of time compression, the latter elements of learning could be compromised. As argued previously, if individual mental models are not as well developed, the concerned personnel may not have good ideas to improve process and product design. In addition, time compression may not facilitate effective communication among personnel, and may result in dysfunctional coordination.

At the organizational level, prior work has argued that unless lessons learnt from experiments are transformed into routines and processes, the benefit of experience may be lost (Zollo and Winter, 2002; Gibson and Vermeulen, 2003; Argyris and Schon, 1978). Time compression could lead to either extreme reaction – too quick codification of sub-optimal routines or the lack of any routinization at all in the organization (Mihm et al, 2003). These processes may lead to loss of valuable lessons and therefore to poor outcomes for the firm.

Finally, the pressure of maintaining output volumes may simply prevent the organization from setting aside time for regular maintenance or making the changes required for better functioning. For example, a factory that is operating for two shifts a day simply has less opportunities to make layout changes than a factory that operates only one shift a day. Delays and non-implementation of better ideas, though individually small, may cumulatively lead to significant reduction in output quality. Putting these arguments together, we suggest that:

H1: Increasing time for experience accumulation (i.e., reducing time compression) has a positive impact on quality of organizational outcomes.

Interaction effect with complexity: We expect that the impact of time compression on quality outcomes is likely to be exacerbated when the organization's tasks are complex rather than simple. Complex tasks are more likely to require greater levels of expertise to accomplish – individuals likely need more complete mental models and groups may need more effortful coordination – to solve the problems associated with complex tasks.

One of the key benefits of learning is the improvement in individual mental models. When individuals better understand cause-effect relationships, they are more likely to implement processes and procedures that improve outcomes. For example, Pisano (1994; 1996) showed that learning by doing was particularly important in biotechnology processes that were not well understood when compared to chemistry based processes in pharmaceutical companies. Edmondson et al (2003) argues that tacit knowledge based learning is more difficult to accomplish than explicit knowledge based learning; in their empirical analysis they find that late entrants catch-up faster when the underlying knowledge base is more explicit. Haunschild and Sullivan (2002) argued that specialist airlines learnt more from mistakes with more complex causes, since they provided an opportunity for the firm to better understand the interconnections between elements of their operations. Since complex tasks are more likely to require more complete mental models and feature more intricate connections among different components, learning by doing is likely to be particularly more important for complex problems. However, time compression in experience accumulation decreases the likelihood of forming accurate mental models, and it is likely to be a bigger impediment to solving complex problems than for relatively simpler problems.

From a group coordination perspective as well, time compression is likely to lead to more negative outcomes for more complex problems. As discussed earlier, groups are less likely to share information and rely on more appropriate decision-making schemes when constrained for time. In addition, for solving complex problems, apart from sharing information, group members also need to recombine this information in order to understand multiple facets of the problem and generate potential solutions. Gruenfeld and Hollingshead (1993) argue that groups that achieve 'integrative complexity' are better able to solve more complex problems. Integrative complexity is defined as the group's ability to identify and differentiate between different dimensions of a problem and integrate the interconnections between these dimensions, thereby helping groups to develop a more complete understanding of the task. Gruenfeld, Hollingshead and Fan (1995) further explored the formation of integrative complexity and found that only groups that had sufficient time to reflect over their experience achieved the required cognitive synthesis. Hinsz, Tindale and Vollrath (1997) suggest that groups subject to time compression are more likely to have a simpler and narrower perspective on the task than individuals acting alone. This allows groups to act fast, but at the cost of a very incomplete understanding of the problem. Time compression may also lead individuals to be subject to cognitive closure and epistemic freezing, leading to behaviors such as opinion uniformity, in-group favoritism, rejection of deviates, and resistance to change (Kruglanski et al, 2006; Kruglanski and Webster, 1991). These pathologies in both individual and group learning are more likely to result in detrimental outcomes for more complex tasks than for relatively routine tasks. These arguments therefore suggest that:

H2: Reducing time compression in experience accumulation has a more positive impact on quality of outcomes for complex tasks than for simple tasks.

Interaction effect with integrator: Reagans et al (2005) argue that the two factors that give rise to the learning curve are improvements in individual ability and the capacity for coordinated activity. Some prior work suggests that the heterogeneity in learning curves between firms engaged in exactly the same learning task could be attributed to differences in coordination ability (e.g., Pisano et al, 2001). For example, Edmondson, Bohmer and Pisano (2001) show that surgical teams learning a new surgical routine performed better with experience when they were able to coordinate well among themselves. Faraj and Xiao (2006) and Huckman, Staats and Upton (2009) showed that investments in achieving efficient coordination such as investing in learning shared processes and routines or staffing teams with members with prior experience who have already learnt to coordinate among themselves improved performance in hospital emergency response crews and in software development teams. Boh et al (2009) show that at the individual level, specialized task experience is an important determinant of performance improvements, but at the organizational level, it is the variety of tasks performed that is important. They argue that task variety, at the expense of specialization, improves organizational performance, since it improves coordination among the different team members. Argote and Ren (2012) argue that joint work experience over time creates transactive memory systems (TMS) that lead to improved performance due to better coordination.

As argued above, time compression in experience accumulation is likely to lead to poor coordination among individuals in an organization because of ineffective information transfer and potentially incomplete knowledge of the nature of interdependence between the sub-tasks performed by different individuals and groups. These firms are likely to suffer poor outcomes caused by coordination failures that arise from miscommunication, misunderstandings and delays (Srikanth and Puranam, 2011).

Organizations employ integrators in order to facilitate coordination between interdependent individuals. Integrators, since they specialize in achieving coordination, are more likely to spot opportunities to improve processes such that specialists' activities are better aligned. This may allow the integrator to mitigate coordination problems that arise from turnover, for example. In some circumstances, the integrator could also become an agent for the spreading of best practices across the organization by observing areas where work is accomplished efficiently and bringing these new ideas to the notice of others in the organization who could benefit from these changes. For example, an integrator may more clearly assign tasks across experts and coordinate their activities instead of waiting for a TMS to develop with time. The role of the integrators necessarily involves them having a broader outlook of the tasks involved, which they can use to prevent other group members from having an overly narrow and ill-formed mental model even under time compression. Lapre and Van Wassenhove (2001) argue that integration between departments at the factory level leads to reduced waste and improved quality, but these lessons from experience are also the most difficult to implement. Integrators, by their very job description, are required to facilitate such implementation since they are likely to have a good idea of how any change affects interdependence and therefore facilitate coordinated adaptation. Integrators therefore help in achieving better communication and coordination through knowledge codification and routinization, the two components of learning that are compromised by time compression. Based on these arguments, we hypothesize that:

H3: Reducing time compression in experience accumulation has a more positive impact on quality of outcomes for organizations that do not employ integrators than for organizations that employ integrators.

METHODS

Empirical Setting

The setting of fertility care is ideally suited to test our hypotheses. The task of completing an in-vitro fertilization (IVF) treatment cycle for the female patient consists of several stages (i.e., ovarian stimulation, egg extraction, gamete manipulation, and embryo transfer), and requires the joint participation of medical personnel coming from several areas of specialization including gynecology, embryology, endocrinology and nursing. It is important to note that IVF treatment continues to be a highly uncertain with many biological, physiological and clinical variables confounding the outcome of the interventions. In addition to the unknown biological factors that routinely confound the response to treatment, coordination failures among the interdependent specialists having different domains of action is also fairly prevalent in the medical domain (Briscoe, 2007; Cohen & Hilligoss, 2010; Solet, Norvell, Rutan, & Frankel, 2005). For example, IVF cycles require members of staff to leverage technology and know-how within their specializations (such as endocrinology or embryology), while also coordinating patient handoffs with each other. Due to tensions between the timing of patient visits and internal rota systems, such handoffs are often problematic over the typical two-month treatment period. IVF therefore can be considered a fairly nascent field that provides significant opportunities for learning by doing. Since there is considerable demand for IVF treatment, often clinics face the choice between admitting additional patients at the risk of overburdening their staff vs. refusing new patients and foregoing additional revenue. In our data there is a fair amount of heterogeneity in the number of patients treated by clinics after controlling for their size, allowing us to test our hypotheses.

Sample and Data

Our data was obtained from the Human Fertilization and Embryology Authority (HFEA) in the UK to which all fertility clinics in the UK are obligated to report details of their operations for regulatory purposes. Since we obtained data from the regulatory authority we capture the entire population of fertility clinics in the UK. The data reported by the clinics to HFEA include the number of patients treated that year, patient outcomes, general profile of patients, and technologies used. These data are reported by the clinics to HFEA every year. This rich longitudinal data allows us to isolate the effects of time compression in experience accumulation on operational performance and output quality after controlling for a large number of confounding variables.

In the United Kingdom, clinic-level indicators for all IVF providers have been recorded since 1992, allowing us to avoid the bias of left censoring and selection bias that usually hamper analyses employing cumulative experience as an independent variable. However, since clinic size is available only since 1998, the findings in this study concern only the more recent part of the learning curves observed in this domain, thus reflecting a more mature stage of the technology and flatter slopes than in the early 1990s.

This study includes the prior experience of all UK medical clinics that provided IVF from 1998 to 2006. The unit of analysis is the IVF clinic-year and the total number of clinics with at least three consecutive years of performance data is 84, with a final sample of 561 clinic-years. The information in the HFEA database and patient guides has been collected annually and is subject to regular verifications during internal audits and onsite inspections. The data allows us to conduct analyses with clinic-year as the unit of observation.

Dependent variables. To explain variance in operational performance across clinics we use the log transformation of the number of live-birth events at each clinic in a given year. The dependent variable essentially captures the number of successful treatments in a given clinic-year. We control for the total number of patients treated in that clinic-year in the RHS.

Independent variables: Our argument is that accumulating high level of experience in a short period of time is detrimental to organizational performance. We measure this by interacting cumulative experience accumulated by the firm with the firm's age in years, which is the time it took to cumulate that level of experience; our argument is that this interaction effect should have a positive sign. Note that since we argue for this interaction effect, the main effects of experience and time could be positive or negative.

To measure clinic cumulative experience, we follow the learning curve tradition by cumulating all prior IVF cases since clinic founding until but not including the focal year and standardizing the log-linear transformation of the values (Epple, Argote and Devadas, 1991; Argote, 1999; Stan and Vermeulen, 2012). Experience accumulation time is the number of years since founding until but not including the focal year, and is also standardized.

Complexity: To test hypothesis 2, we measure complex cases as the percentage of female patients above age 35 treated in the clinic. Since the chance of success through IVF decreases sharply after the age of 35 (Sharif & Afnan, 2003 pp. 484), treating older women represents a challenge to clinics, requiring more sophisticated tools and cognitive resources on behalf of the staff than younger patients.

Coordination: As argued above, coordination among the multiple specialists is a significant challenge in fertility treatment. In our data, some clinics had a defined integrator role, either a nurse or a physician, who was responsible for shepherding a patient across the multiple specialists and ensuring that all vital information about these patients was transferred to the different specialists across the several IVF treatment stages. To test hypothesis 3, the availability of integrators at each clinic is specified; 0 if no integrator role is present representing low efforts at coordination and 1if there is an integrator, representing high efforts at coordination. Surprisingly, this feature of organizational design displays very low within-clinic variation with no instances of integrator adoption and only six clinics eliminating the option of offering integrators within the window of observation. To improve the empirical strategy and clarity of our results, we tested our results by excluding these clinics (21 observations) from the sample; our results are robust to their inclusion.

Control Variables: First we control for the nature of patient intake by controlling for the proportion of patients above age 35, since this could influence the overall success rate of the clinic. Since larger clinics can see more patients, we needed to control for clinic size. As a proxy for clinic size we collected data on the number of specialist roles reported to the HFEA by each clinic on a yearly basis; this data has been collected by the HFEA only since 1998. Therefore, in our main specifications we only use data from 1998 until 2006. To control for the nature of the IVF technology used, following Stan and Vermeulen (2012), we specify the percent of cycles which involved a more invasive version of IVF during the year of observation (i.e. intra-cytoplasmic sperm injection). We also include a variable that accounts for the learning environment of each clinic, as better learning environments lead to better outcomes; this measure is a count of research projects that have been accredited by the HFEA and undertaken at the focal center yearly.

To account for industry trends, we include a measure of industry-level experience which consists of a log transformation for the count of patients treated in the UK prior to the year of observation. Moreover, a binary variable labeled post-2001 is also included to account for the occurrence of a regulatory shock in year 2001, which restricted the number of embryos that were allowed to be placed back into the patient to a maximum of two per IVF cycle started (HFEA, 2001).

Estimation technique: Following Epple, Argote and Devdas (1991), the learning curve estimation for clinic i at time t is written as (1).

$$clinic\ productivity_{it} = \frac{total\ birth\ events(B)_{it}}{total\ patients\ treated(W)_{it}} = AQ_{it-1}^{\lambda}e^{\epsilon_t} \quad (1)$$

where A is a constant, λ is the clinic's learning rate and ϵ_{it} is the error term representing random factors affecting the treatment process. Our argument is that productivity also depends on the speed with which this experience has been accumulated; the age of the firm acts a proxy for how fast the firm has accumulated Q units of experience. We take logs and recast (1) as follows:

$$\ln B_{it} = lnW_{it} + \lambda lnQ_{it-1} + lnA + \epsilon_{it} \quad (2)$$

where lnA is a constant estimated as the clinic fixed effect, and λ is the learning parameter estimated in traditional learning curve models (Epple at l, 1991; Darr et al, 1995). Taking into account our theory on the effect of experience accumulation time on experience, following the formulation by Dierickx and Cool (1989), we treat the effect of time compression as an interaction effect of time with experience. Adding this term we get:

$$\ln B_{it} = lnW_{it} + lnW_{it}sq + \lambda lnQ_{it-1} + \alpha time_{it-1} + \beta lnQ_{it-1} * time_{it-1} + lnA + u_{it} \quad (3)$$

This estimation model is similar to the one used by Stan and Vermeulen (2012) in their estimation of the learning curve. Our theory is that β is positive. We used an OLS to estimate (3).

RESULTS

Table 1 shows the descriptive statistics, including mean, standard deviation, minimum and maximum values for the variables of interest in our estimations. We see that there is adequate variation in the key independent variables and the two dependent variables – successful patient outcomes and the quality of patient outcomes. Table 2 shows the correlations between these variables. As expected, there is very high correlation between cumulative experience of the firm and the time in which this experience was accumulated.

We next turn to the regression models to test our hypotheses. From Model 1 in table 3 we see that impact of prior experience and time on patient outcomes is not significant, though the impact of age is positive and significant. We expect this, because our argument is that it is only firms that have paced their experience accumulation that really benefit from experience. In model 2, we enter the interaction terms between cumulative experience and experience time. As expected, the interaction term is positive and significant, supporting hypothesis 1. In this model, we also note that the effect of cumulative experience has become positive and significant, whereas the effect of time is not significant. Figure 1 graphically shows the impact of increasing time for experience accumulation on patient outcomes. This plot is on a log-log scale; as expected we see that firms that have taken more time to accumulate a given volume of experience have superior performance – their learning curve is parallel to and above that of firms that have taken lesser time.

To test the impact of complexity, first we split the sample at the median level of complexity in to sub-samples with lower vs. higher levels of complexity. Model 3 and Model 4 test the impact of time compression on the low and high complexity sub-samples respectively. In both model 3 and model 4, the interaction effect of experience and time is significant; however the main effect of experience is only significant in model 3, it is barely significant in model 4. The coefficient of the interaction term, in model 4 is larger than in model 3, as hypothesized, but it is not significantly different. This presents conflicting patterns of evidence. Therefore, as an additional step, we ran a model that includes a 3-way interaction between experience, accumulation time and complexity. In model 5, we see that none of the interaction terms are significant by themselves; the experience*accumulation time coefficient has also lost significance in this model. This is to be expected, because of high levels of multicollinearity among the interaction terms. However, a joint test of the two terms of interest to us – the interaction term between experience and accumulation time, and the 3-way interaction term are together highly jointly significant with $F(2, 442) = 7.41$; p-val = 0.0007. This suggests that there is indeed a three way interaction effect – that the impact of time compression in experience accumulation is likely to be more severe for clinics that handle more complex cases, though the data suggests that this impact may not be very large.

To test the impact of integrator, we again split the sample into firms that do not employ an integrator (model 6) vs. firms that do so (model 7). From model 6, we see that the the interaction effect with time is positive and significant in the no-integrator sub-sample. However, it is not significant in the sub-sample of clinics that employ an integrator. This suggests that only firms that employ an integrator more effectively learn from their experience, whereas those that have poor coordination ability (lack of an integrator) are more subject to the negative effects of time compression. This suggests support for hypothesis 3.

Robustness Checks

We performed a number of robustness checks on our results. First we checked to see whether clinics that choose easier patients to work with had better outcomes and if that is driving our results. Fertility treatment is provided both by private clinics who have the ability to screen patients and accept only those that are more likely to have positive outcomes. Though this could impact overall success rates of the clinic, it is unclear why this selection should matter for the interaction effect between time and experience, which is our theoretical contribution. After all, if we see a significant and positive interaction effect, this suggests that even these clinics that screen their patients are also subject to time compression diseconomies. However, we checked our main result in a sub-sample of NHS clinics. NHS is UK's public health service and by law they may not turn away any patients who come to them for fertility treatment. Our results hold in this sub-sample[4].

Next, we checked to understand whether the quality of the clinic, potentially in terms of more skilled doctors and other professionals, is driving our results. Theoretically, high quality clinics should be subject to time compression just like low quality clinics, as long as they learn from experience, though the impact maybe lower. In order to test for this possibility, we included the quality obtained by the clinic in the previous year (Clinic Quality_{t-1}), measured as the ratio of live births to women treated, as an additional control in the regression. If clinic quality is driving our results, previous year's quality should explain success rates in the current year, and cumulative experience and its interaction with time should not matter. In table 4, we report the results of the regressions with this additional control. Though we see that previous year's quality is positive and significant, the results for our theory variables are qualitatively identical to the results reported in table 3 across all conditions, suggesting that our results are robust to this concern.

DISCUSSION

Since learning by doing is one of the most important means available for firms to develop capabilities, understanding the factors that lead to heterogeneity in learning from

[4] We cannot perform the sub-sample analysis on complexity and the presence of an integrator in the NHS only sub-sample, since for some analyses the number of observations drops drastically (to less than 100).

experience enables us to understand when firms may out-perform or under-perform their peers in capability development (Teece 2007; Felin and Foss, 2012; Winter, 2012). Prior empirical work has found that different organizations engaged in the same task have very different learning curves (Argote and Epple, 1990; Hayes and Clark, 1986; Pisano et al, 2001). Understanding the factors that influence the learning curve, and therefore capability development is one of the fundamental problems in strategy research. It is from this perspective that our study makes novel contributions.

We find that clinics that accumulate experience in a short period of time perform poorly when compared to firms that accumulate the same level of experience over a longer time period. In our estimation, when experience increases by one standard deviation, the number of live births increases by 54%; when this increase is accomplished by a firm that is one standard deviation (3.7 years) older than the mean (10 years), the number of live births further increases by about 42%. We also find that this 'time compression' effect is significantly exacerbated for clinics that treat more complex conditions. We also find very interesting effects for impact of presence vs. absence of an integrator to clinic outcomes, very similar to the effects we find for complexity. These results in combination uncover important contingent effects that help us understand why learning curves across firms maybe very different.

Prior work has suggested that differences in learning curves across firms performing the same task arise from scope economies or from differences in turnover (Argote, 1999; Hayes and Clark, 1986; Dutton and Thomas, 1984). In contrast to these explanations, we show that the speed of experience accumulation itself influences how deep or shallow the experience curve is. Some studies show that firms learn more from solving more complex problems (Haunschild and Sullivan, 2002; Stan and Vermeulen, 2012). Our result on the contingent effect of speed on firms that handle more complex cases adds further nuance to these findings.

Our work also has interesting implications for the relationship between time and strategy, one of the more neglected topics in our field. Prior work on time compression in capability learning has focused mostly on its existence and its impact on competitive advantage. For example, Fine (1998) speaks of industry clock-speed and its impact on competition in the industry. Koeva (2000) and Pacheco-de-Almeida et al (2008) document differences in time-to-build new plants. Prior work does not examine the factors that influence whether TCD is high or low.

Our effort throws some light on these issues. We find that depending on the types of tasks and the coordination ability of firms, firms within the same industry may be subject to higher or lower levels of time compression. Our theory allows us to suggest that time compression is more likely to be a problem when both individuals learning and group coordination are significant for firm performance. This allows us to speculate the conditions under which TCD is likely to be larger vs. smaller. For example, if the new capability developed is an incremental innovation, TCD for an imitator/late-entrant may not be significant. On the other hand, if the innovation is a significant leap over existing knowledge, it may be more difficult for an entrant to catch up to the incumbent. Edmondson et al (2003) also show that innovations that rely more on tacit knowledge that is more difficult to transfer are likely to be less easily imitated.

This adds a different mechanism for explaining why business model innovations such as the Toyota Production System are more sustainable. It is just not cognitive inertia or lack of a fine understanding of the inner workings of the innovation (Henderson and Clark, 1990; Tripsas and Gavetti, 2000; Chesbrough and Rosenbloom, 2002; Chesbrough, 2010), but simply the passage of time required to attain the benefits from implementing these innovations. This is a promising direction for future research.

Finally, our work has implications for long-term vs. short-term trade-offs in firm strategy. Prior work suggests that firms often embark on strategies that fulfill short-term goals such as increased profits, but at the expense of long-term goals such as survival. For example, Benner and Tushman (2002; 2003) show that adoption of ISO 9000 practices led to short-term increases in profits and quality, but at the expense of a long-term reduction in innovation. Similarly, other studies have shown that aggressive outsourcing strategies can benefit short term benefits at the expense of long term survival (Reitzig and Wagner, 2010; Becker and Zirpoli, 2011). Guthrie and Datta (2008) showed that downsizing programs lead to short term profitability at the expense of long-term benefits that accompany employee engagement and stability. Our results suggest that clinics that expand too aggressively may have improved revenue in the short term but suffer from poor capabilities in the longer term. The impact of such decisions in different technology regimes and at different periods in the industry life cycle are important directions for future research.

Our work is subject to the following limitations. Because the data for the study were from a single industry, one potential limitation relates to the generalizability of the findings to other industries. Most prior research in learning curves have been in the manufacturing industries. Though the theoretical mechanisms at play are likely to be robust to the context of study, we do not know whether context makes a difference to how important time compression and its moderators are to performance outcomes. Finally, our data are not fine grained enough to understand how the learning parameter (λ) changes with time compression. A true test of the model would require that λ decreases with speed of experience accumulation. This would involve computing the learning curve for every single clinic and understanding how sensitive this λ parameter is to changes in speed of experience accumulation, for example, such as those accompanied by unexpected fluctuations in volume (cf: Kc and Terweisch, 2009). Future work with more fine grained data should look at this issue.

Despite the above limitations, our work does have some strengths. It is the first study that we know of that investigates the impact of speed of experience accumulation on organizational learning curves. We also investigate contingent effects for when time compression effects are mitigated vs. loom larger. Our estimations are robust to a variety of checks, including controlling for prior quality of the clinic. Investigating learning curves and why they vary across firms in the same industry in a service context adds further to our understanding of service businesses, which have hitherto been less well investigated when compared to manufacturing.

CONCLUSIONS

In this paper we investigate the effect of time compression in experience accumulation on the operating performance of fertility clinics in the UK. We find that time compression is associated with poor operational outcomes; we also find that this effect is exacerbated for clinics that treat more complex cases. We also find that there is greater learning from experience in clinics that employ an integrator to facilitate coordination among specialists. We argue that time compression impacts both the components of the learning curve: the improvement in individual ability and improvements in the organization’s coordination competence. We argue that the adverse impact of time compression on the learning curve is one mechanism that underlies time compression diseconomies.

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Table 1: Descriptive Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
# live birth events$_t$	549	85.24	74.03	0	512
# of women$_t$	550	329.90	251.45	8	1467
Log(CumExp)$_{t-1}$	550	8.16	1.12	4.13	10.14
Experience Accumulation Time$_{t-1}$	550	10.17	3.79	1	16
Complexity$_t$	550	0.50	0.09	0.23	0.84
ICSI tech usage$_t$	550	0.37	0.15	0	0.79
Research projects$_t$	550	0.36	0.81	0	5
Size$_t$	550	2.10	0.91	0	5
Log(Industry Exp)$_t$	550	12.16	0.28	8.57	12.53
Post-2001	550	0.60	0.49	0	1

Table 2: Correlation Table

		1	2	3	4	5	6	7	8	9	10
# live birth events$_t$	1	1.00									
# of women$_t$	2	0.95	1.00								
Log(CumExp)$_{t-1}$	3	0.65	0.72	1.00							
Exp Acc Time$_{t-1}$	4	0.38	0.41	0.77	1.00						
Complexity$_t$	5	0.21	0.18	0.16	0.17	1.00					
ICSI tech usage$_t$	6	0.36	0.32	0.24	0.15	0.17	1.00				
Research projects$_t$	7	0.28	0.33	0.36	0.24	0.00	0.09	1.00			
Size$_t$	8	0.34	0.34	0.42	0.37	0.13	0.39	0.14	1.00		
Log(Industry Exp)$_t$	9	0.17	0.14	0.21	0.44	0.35	0.39	0.04	0.27	1.00	
Post-2001	10	0.15	0.12	0.19	0.40	0.34	0.37	0.03	0.21	0.73	1.00

TABLE 3: Predicting Log(# Live Birth events) – OLS estimation with clinic fixed effects

VARIABLES	(1) main	(2) TCD	(3) low complex	(4) high complex	(5) 3-way interaction	(6) No Integrator	(7) Integrator
Ln(# of women$_t$)	2.010***	2.133***	2.293***	1.798***	2.155***	2.672***	0.269
	(0.192)	(0.193)	(0.344)	(0.350)	(0.195)	(0.256)	(0.329)
Ln(# of women$_t$) sqr	-0.08***	-0.01***	-0.11***	-0.06*	-0.10***	-0.16***	0.07**
	(0.021)	(0.021)	(0.035)	(0.036)	(0.021)	(0.028)	(0.032)
ICSI tech usage$_t$	0.087	0.152	0.240	-0.033	0.156	0.309	0.321*
	(0.154)	(0.153)	(0.210)	(0.254)	(0.153)	(0.254)	(0.179)
Research projects$_t$	0.009	0.007	0.004	0.037	0.009	-0.008	0.046
	(0.028)	(0.027)	(0.036)	(0.047)	(0.027)	(0.036)	(0.042)
Complexity$_t$	-0.41*	-0.32			-0.25	-0.04	-0.96***
	(0.247)	(0.245)			(0.290)	(0.394)	(0.288)
Industry Exp$_t$	-1.216	-1.013	-0.444	-1.558	-1.090	-2.888**	0.262
	(0.790)	(0.782)	(1.227)	(1.301)	(0.796)	(1.256)	(0.920)
Post-2001	-0.085*	-0.070	0.001	-0.126$	-0.072	-0.176**	0.040
	(0.050)	(0.050)	(0.082)	(0.077)	(0.050)	(0.081)	(0.057)
Size$_t$	-0.034	-0.029	0.012	-0.070*	-0.032	-0.029	-0.027
	(0.026)	(0.026)	(0.045)	(0.040)	(0.026)	(0.043)	(0.029)
Log(CumExp)$_{t-1}$	-0.017	0.459***	0.683***	0.616*	0.793**	0.615*	0.303*
	(0.078)	(0.154)	(0.246)	(0.321)	(0.397)	(0.325)	(0.154)
Exp Acc Time $_{t-1}$	0.698*	0.299	-0.114	0.464	0.336	1.155*	-0.191
	(0.389)	(0.400)	(0.666)	(0.637)	(0.472)	(0.651)	(0.465)
Log(Exp)$_{t-1}$*Time$_{t-1}$		0.241***	0.245**	0.370***	0.168†	0.301**	0.099
		(0.067)	(0.119)	(0.120)	(0.220)	(0.135)	(0.074)
Exp*Complexity					-0.671		
					(0.635)		
Time*Complexity					-0.010		
					(0.357)		
Exp*Time*Complexity					0.202†		
					(0.345)		
Constant	10.213	7.274	-0.210	14.501	8.118	28.007*	-2.403
	(9.447)	(9.360)	(14.779)	(15.462)	(9.512)	(14.949)	(11.085)
Observations	540	540	271	269	540	264	267
R-squared	0.748	0.755	0.710	0.669	0.756	0.816	0.658
Number of clinic	84	84	66	67	84	38	41
Bet R-Sq	0.72	0.80	0.88	0.73	0.79	0.48	0.92
F	132.4***	124.7***	47.6***	38.8***	97.9***	86.9***	37.6***

*** p<0.01, ** p<0.05, * p<0.10,

†: Joint test that both coefficients are zero: F(2, 442) = 7.41; p-val = 0.0007

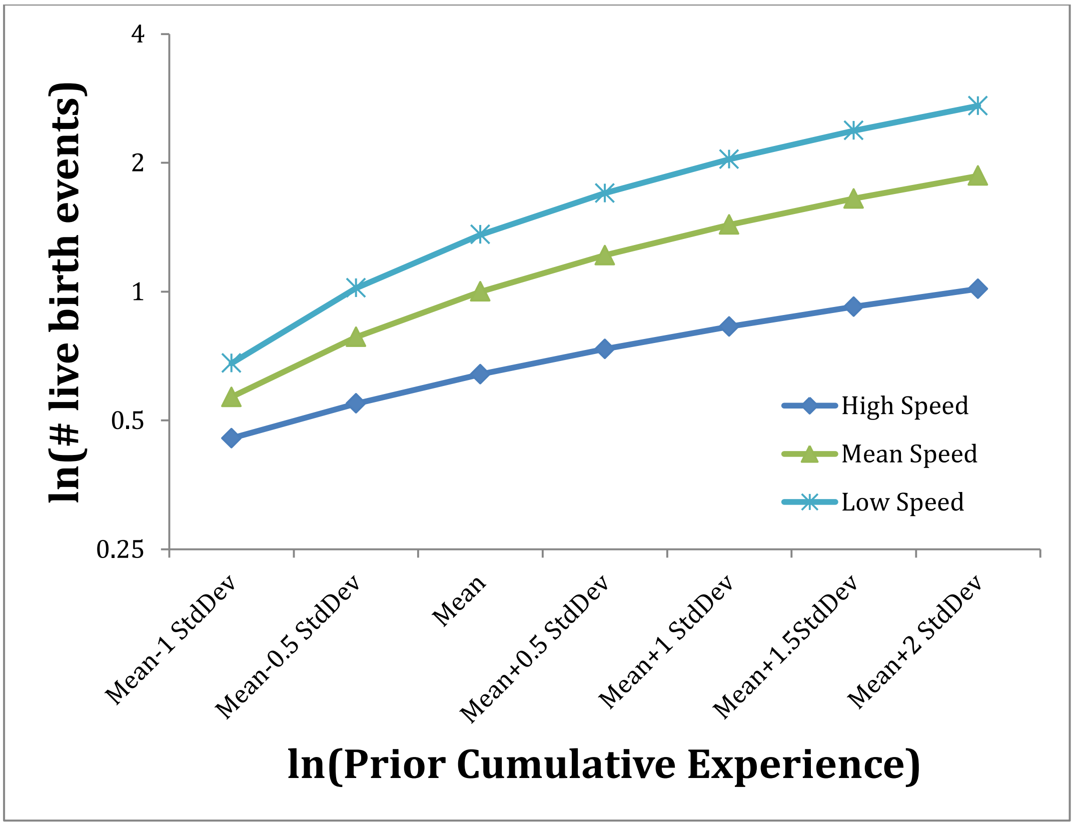
Table 4: Predicting Log(# Live Birth events) after controlling for clinic quality – OLS estimation with clinic fixed effects

VARIABLES	(1) main	(2) TCD	(3) low complex	(4) high complex	(5) 3-way interaction	(6) No Integrator	(7) Integrator
Ln(# of women$_t$)	2.011***	2.137***	2.308***	1.838***	2.159***	2.701***	0.269
	(0.191)	(0.192)	(0.344)	(0.347)	(0.194)	(0.251)	(0.330)
Ln(# of women$_t$) sqr	-0.08***	-0.01***	-0.11***	-0.07*	-0.10***	-0.16***	0.07**
	(0.021)	(0.021)	(0.035)	(0.036)	(0.021)	(0.028)	(0.032)
ICSI tech usage$_t$	0.072	0.138	0.226	-0.028	0.141	0.195	0.321*
	(0.153)	(0.152)	(0.211)	(0.251)	(0.152)	(0.252)	(0.179)
Research projects$_t$	0.011	0.009	0.007	0.035	0.011	0.001	0.046
	(0.027)	(0.027)	(0.036)	(0.047)	(0.027)	(0.036)	(0.042)
Complexity$_t$	-0.376	-0.287			-0.192	0.019	-0.96***
	(0.246)	(0.244)			(0.290)	(0.387)	(0.289)
Industry Exp$_t$	-1.367*	-1.167$	-0.457	-1.960$	-1.256$	-2.886**	0.265
	(0.789)	(0.780)	(1.228)	(1.303)	(0.794)	(1.232)	(0.931)
Post-2001	-0.085*	-0.069	0.000	-0.126$	-0.072	-0.147*	0.041
	(0.050)	(0.049)	(0.082)	(0.076)	(0.050)	(0.080)	(0.057)
Size$_t$	-0.033	-0.027	0.013	-0.069*	-0.031	-0.020	-0.027
	(0.026)	(0.025)	(0.045)	(0.039)	(0.026)	(0.042)	(0.029)
Clinic Quality$_{t-1}$	0.579**	0.606**	0.335	0.817**	0.598**	1.177***	-0.008
	(0.247)	(0.243)	(0.361)	(0.382)	(0.245)	(0.384)	(0.290)
Log(CumExp)$_{t-1}$	-0.052	0.433***	0.693***	0.605*	0.774*	0.619*	0.304*
	(0.079)	(0.153)	(0.247)	(0.318)	(0.394)	(0.319)	(0.156)
Exp Acc Time $_{t-1}$	0.763*	0.359	-0.127	0.636	0.392	1.085*	-0.192
	(0.388)	(0.399)	(0.666)	(0.636)	(0.470)	(0.639)	(0.470)
Log(Exp)$_{t-1}$*Time$_{t-1}$		0.246***	0.261**	0.366***	0.215†	0.334**	0.099
		(0.067)	(0.120)	(0.119)	(0.219)	(0.132)	(0.074)
Exp*Complexity					-0.655		
					(0.631)		
Time*Complexity					-0.004		
					(0.355)		
Exp*Time*Complexity					0.131†		
					(0.344)		
Constant	11.893	8.972	-0.181	19.069	9.947	27.652*	-2.442
	(9.427)	(9.331)	(14.784)	(15.468)	(9.488)	(14.667)	(11.202)
Observations	540	540	271	269	540	264	267
R-squared	0.751	0.758	0.711	0.677	0.760	0.824	0.658
Number of clinic	84	84	66	67	84	38	41
Bet R-Sq	0.71	0.79	0.88	0.69	0.78	0.52	0.92
F	122.0***	116.1***	43.4***	36.4***	92.9***	83.5***	34.3***

*** p<0.01, ** p<0.05, * p<0.10,

†: Joint test that both coefficients are zero: F(2, 441) = 7.65; p-val = 0.0005

Figure 1



ln(# live birth events)
4
2
1
0.5
0.25
High Speed
Mean Speed
Low Speed
Mean-1 StdDev
Mean-0.5 StdDev
Mean
Mean+0.5 StdDev
Mean+1 StdDev
Mean+1.5StdDev
Mean+2 StdDev
ln(Prior Cumulative Experience)