The Origins of Time Compression Diseconomies

ABSTRACT

Research Summary: That capability development is subject to time compression diseconomies (TCD) is well-known in the strategy literature. However, so far, there is limited attention paid to its origins, i.e., why it exists, and demonstrating it empirically. In the context of fertility clinics in the UK, we show that faster experience accumulation is associated with lower success rates; i.e., time compression in experience accumulation results in shallower learning curves. We also show that TCD 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. We propose differential learning rate as the mechanism that underlies TCD, and develop implications for firm capabilities and sources of competitive advantage.

Managerial Summary: As firms pursue new opportunities, it is intuitive to grow fast. Rapid growth has many advantages, including a quicker payback on investment as well as garner first mover advantages. However, there can also be a dark side to such high paced growth. By analyzing data on *in-vitro* fertilization clinics in the UK, we show that clinics that grew the fastest were slower in improving their treatment success rates, while slower growing clinics improved more with increasing experience. This penalty of rapid growth is more severe for clinics that treat more complex cases, but it can be ameliorated by better coordination between specialist activities. Our research serves as a warning that faster isn't always better.

INTRODUCTION

One of the most important issues in strategy research is the concept of time-compression diseconomies (TCD). Dierickx and Cool (1989) introduced the concept of TCD by explaining, "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" (p. 1507). TCD holds that firms are constrained in their ability to develop or imitate capabilities at least in the short-run. Despite the importance of TCD to the idea of sustainable competitive advantage, few studies have empirically examined TCD, and none have explored its origins. In this paper, we directly test for the existence of TCD in the population of fertility clinics in the UK and speculate on its potential origins and underlying mechanisms.

Thus far, there has been surprisingly little empirical work on TCD, and existing studies have reached mixed conclusions. Hawk, Pacheco-de-Almeida, and Yeung (2013) have shown that the cost of building petrochemical plants increases as time is compressed, though firms may ultimately benefit from speeding up (Hawk & Pacheco-de-Almeida, 2018). Knott, Bryce, and Posen (2003) have demonstrated that TCD has a very limited effect on catch-up ability in the pharmaceutical industry, whereas Vermeulen and Barkema (2002) and Jiang, Beamish, and Makino (2014) have illustrated that speed negatively influences success in international expansion. In a recent review of the work on TCD, Hawk and Pacheco-de-Almeida (2018) conclude, “In sum, TCD have been a longstanding theoretical principle with important implications for multiple strands of literature in management science; yet, we have only sparse and outdated empirical evidence of their existence” (p. 2491). Thus, further empirical work on TCD is warranted.

Further, current empirical work does not explore the mechanisms that cause TCD. Without a causal theoretical mechanism, we are unable to predict the conditions under which the (presumably negative) effect of time compression on performance is exacerbated or mitigated. We propose such a mechanism by positing that time compression in accumulating experience compromises learning by doing, resulting in shallower learning curves.

Accumulating experience with the focal task, or learning by doing, serves as one of the most important ways in which firms develop capabilities (Arrow, 1962; Nelson & Winter, 1982; Winter, 2000). It is widely accepted that heterogeneity in firms’ learning curves can underlie competitive advantage (Argote, 2012), which may be temporary or permanent (Rockart & Dutt, 2015). From this perspective, TCD arises if fast experience accumulation leads to shallower learning curves (i.e., a lower rate of capability development). Although the idea seems intuitive, prior work has not empirically tested it before or considered factors that may moderate this effect.

The learning curve literature has measured adaptation rate (Levy, 1965; Lapre & Tsikriktsis, 2006) or learning rate (Argote, 2012) as the slope of the outcome variable (y) with respect to cumulative volume (Q) or $\partial y / \partial Q$. In this paper, we are interested in the slope of the outcome variable with respect to both Q and time taken (t) to accumulate Q; i.e., $\partial^2 y / \partial Q \partial t$. We suggest that the relationship between cumulative volume and outcomes (cost/quality in typical learning-curve research) is moderated by the time taken by the firm to accumulate that level of experience. If TCD exists, the shorter the time, the shallower the learning curve, meaning the less positive the relationship between volume and a desirable outcome.

We investigated this question using data from fertility clinics in the UK. We show that the more time a clinic takes to accumulate a given volume of experience, the higher its level of successful treatments becomes. In other words, we show that clinic age positively moderates the basic volume-outcome relationship in the learning curve. We also show that the positive moderating effect of time increases for clinics that handle more complex cases but decreases when the clinic employs an "integrator": a staff member who coordinates the work of different specialists involved in the fertility treatment process. As an alternative specification, we directly tested for TCD by computing a measure for speed of experience accumulation and showed that this measure is negatively associated with successful treatments.

We find that (1) time compression in experience accumulation reduces the rate by which firms' capabilities improve; i.e., TCD leads to shallower learning curves. (2) TCDs are partly caused by reduced learning and partly by coordination problems. Finally, utilizing the method suggested by Rockart and Dutt (2015), we found that time compression in experience accumulation only changes the rate of learning and does not influence the maximum attainable capabilities. Thus, in our context, TCD does not result in sustained competitive disadvantage.

PRIOR RESEARCH ON TIME-COMPRESSION DISECONOMIES

Although TCD is an important concept, there is limited research on TCD, which has almost exclusively concentrated on its consequences rather its origins. TCD is one of the causes of resource immobility and therefore contributes to competitive advantage. Without TCD, firms would be able to engage in “backward induction” from product markets to strategic factor markets on a continuous basis, leading to the erosion of competitive advantage (Pacheco-de-Almeida & Zemsky, 2003, 2007). In other words, in the resource-based view, TCD is a critical component of competitive advantage, although, thus far, there is empirical support for this idea.

In this paper, we build upon two broad themes of work. First, we examine the empirical literature involving the construct of speed and how it influences firm performance. Second, we build on the extensive literature on learning curves that has meticulously documented learning-by-doing across a wide range of activities (see Argote, 2012, and Argote, Lee & Park., 2020 for recent reviews), which we utilize to explain why time compression negatively influences the rate of capability development. We review these bodies of literature briefly.

A small body of work examines how speed in performing activities influences firm performance, mainly from a project management or operations viewpoint. Hawk et al. (2013) show that the faster a petrochemical plant is built, the higher its cost becomes. Reduced time implies tighter coordination needs, parallel rather than sequential development, and lower constraints on errors, requiring slack resources, which leads to escalating costs (Carroll et al., 2004). However, Hawk and Pacheco-de-Almeida (2018) demonstrate the existence of time compression *economies* rather than *diseconomies* in the context of building projects. These studies focus on operational projects rather than capability building, and their results are difficult to interpret in terms of why TCD results in poor capabilities and whether or not they are sustained or temporary.

Knott et al. (2003) show that investments in R&D are subject to weak TCD in regard to sales growth for firms in the pharmaceutical industry. The TCD effect plateaus quickly and does not grow strong enough to prevent newcomers from catching up. In this vein, Pacheco-de-Almeida, Hawk, and Yeung (2015) as well as Hawk et al. (2013) show that execution speed—the ability to complete projects quickly—is in itself a capability that confers significant advantage to a firm through its ability to execute projects rather than improve capabilities. However, these studies tell us little about why TCD exists or when it is more or less severe.

In the context of multinationals, Vermeulen and Barkema (2002) show that speed in making foreign acquisitions has a negative effect on the ROA of Dutch multinationals, while Jiang et al. (2014) show that the faster an international subsidiary is established, the less likely its survival, due to stress, chaos, and the overwhelming of managers' cognition. Such studies are subject to the critique by Anand, Mulotte, and Ren (2016) that *selection effects* or unobserved firm-specific factors may be driving the observed variance in speed and its outcomes. They also do not test when and why such effects of speed may be high or low.

Thus, 30 years after the original ideas about TCD were published, the evidence on this critical insight into capability building remains weak. Further, prior work has not examined the micro-level factors that give rise to TCD, determining the mechanism by which time compression hampers the capability development process. We therefore cannot answer questions about the conditions under which the effect of time compression is mitigated and exacerbated with any theoretical insights, nor do we have any conclusive evidence on whether and when TCD gives rise to sustained competitive advantage vs. only a temporary advantage from superior capabilities.

Though intuitive, one potential mechanism—that time compression hinders learning by doing—has not yet been empirically tested. We hone in on this mechanism by building on the extensive research on learning curves in organizations and showing that firms that accumulate experience quickly have shallower learning curves. We also test the same idea through the lens of speed, using the insights from prior studies.

The extensive literature on learning curves broadly connects cumulative output to outcomes such as costs and quality, so it does not help us directly examine TCD, which is ultimately about time compression or speed. However, this literature helps us in two ways. First, it offers us a conceptual basis for why TCD exists by understanding how speed influences learning by doing. Second, it helps identify an empirical methodology to test our hypotheses. We hypothesize that a given level of cumulative experience is more strongly associated with performance when this experience is accumulated slowly.

The learning-curve literature suggests that firms develop capabilities in the process of learning by doing (Argote et al., 2020). Thus, these scholars have theorized how firm capabilities, typically measured as operational outcomes such as cost or quality, change with cumulative volume of production (Wright, 1936; Yelle, 1979). Most of this work treats experience accumulation as reducing the gap between the firm's current capabilities and its maximum potential, such as achieving perfect quality (Levy, 1965; Lapre & Tsikriktsis, 2006). Later work has refined these ideas, particularly by investigating why some firms appear to be more effective at learning by doing than others (see Argote, 2012 for a comprehensive review of this voluminous literature). Scholars have identified many moderators to the basic volume-outcome relationship, broadly classified as task characteristics (Haunschild & Sullivan, 2002; Lapre, Mukherjee, & Van Wassenhove, 2000), task mix (KC & Staats, 2012; Staats & Gino, 2012; Stan & Vermeulen, 2013), and organization structure (Darr, Argote, & Epple, 1995; Epple, Argote, & Murphy, 1996; Huckman & Pisano, 2006; Stan & Puranam, 2017). These studies thus suggest that certain organizational decisions can influence the rate at which firms close the gap between their current and potential capabilities.

Rockart and Dutt (2015) significantly enriched this literature by identifying not only whether firms' decisions change the rate of learning, but also whether they influence the maximum potential capability of the firm. For example, in their work on investment banking, they suggest that firms that work with larger projects are likely to learn more slowly but ultimately reach a higher threshold of capabilities and thus sustained competitive advantage.

We theoretically and empirically build on the substantive learning-curve literature and examine whether time taken for experience accumulation moderates the volume-outcome relationship. In this respect, our theorizing and analysis is similar to prior work on the moderators of the learning curve (Staats & Gino, 2012; Stan & Vermeulen, 2013; Stan & Puranam, 2017) that examines changes to rate of capability development rather than to its level. If experience accumulation time positively moderates the volume-outcome relationship, we can conclude that TCD changes the rate of capability development—which is our intended contribution. We also consider when this moderation effect is high vs. low. In terms of robustness, we implement the empirical strategy proposed by Rockart and Dutt (2015) to identify whether faster vs. slower experience accumulation changes a firm's level of capabilities or its maximum potential, which has implications for whether TCD leads to sustained or temporary competitive (dis)advantage in our specific empirical context.

HYPOTHESES DEVELOPMENT

Scholars have long argued that heterogeneity in the learning curve explains differences in firm capabilities (Argote, 2012). However, this literature has *not* yet investigated how the time to accumulate experience influences learning outcomes. In this study, we propose that experience accumulation time moderates the volume-outcome relationship or the learning curve.

The extensive literature on the learning curve argues that capability development at the organizational level is a composite function of several micro-processes including individual learning, improvements in technology, product and process design, and better coordination between the specialist tasks that underlie the capability (Adler & Clark, 1991; Argote, 2012; Helfat & Peteraf, 2003; Reagans, Argote, & Brooks, 2005). Thus, to understand the micro-foundations of TCD, we need to understand how time compression influences one or more of these constituent processes that underlie the learning curve.

Effect of time compression on individual learning: Studies in psychology demonstrate that time compression is likely to hamper individual skill development, which is an important component of a firm's learning curve (Nelson & Winter, 1982; Adler et al., 2009: see section by Winter). In individuals, learning by doing improves outcomes through two means: enhancing motor skills and dexterity in tasks, and enabling individuals to develop more accurate and complete mental models of the tasks that facilitate more effective problem-solving.

Studies in psychology convincingly argue that time compression negatively affects both of these processes. Having longer times to practice allows learners to develop more complex mental models, which they can use to engage with more complex phenomena (White & Fredericksen, 1986). Developing more complete mental models that incorporate contingent effects requires exposure to a wider variety of problems, which happens not just with more experience, but also with more time (Clancey, 1987; Glaser & Bassok, 1989; White & Frederiksen, 1986). 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 development of expertise takes time

(Charness, Krampe, & Mayr, 1995; Schulz et al., 1994). This holds true for developing cognitive skills as well as motor skills (Ericsson & Lehman, 1996; Shadmehr & Holcomb, 1997). These studies align with Dierickx and Cool's (1989) intuition that "MBA students may not accumulate the same stock of knowledge in a one-year program as in a two-year program, even if all inputs other than time are doubled" (p. 1507).

Effect of time compression on improvements in technology, product, and process design: Second, time compression in capability development is also likely to have negative effects on 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. Further, when individuals are performing under heavy workload conditions, they may have less time to think about process improvements or to meet, share lessons learned, and generate best practices (Scott et al., 2006).

Further, prior work has argued that organizations learn improved techniques, such as new designs and processes, through a process of experimentation, communication, and knowledge codification (Gibson & Vermeulen, 2003; Prencipe & Tell, 2001). Prior work has argued that unless lessons learned from experiments are transformed into routines and processes, the benefit of experience may be lost (Argyris & Schon, 1978; Gibson & Vermeulen, 2003; Zollo & Winter, 2002). Time compression could compromise these processes—either by too-quick codification of suboptimal routines or the lack of any routinization at all in the organization (Klein, Conn, & Sorra, 2001; Mihm, Loch, & Huchzermeier, 2003; Lapre & Van Wassenhove, 2001, 2003). These processes may lead to the loss of valuable lessons, and therefore, to poor outcomes.

Effect of time compression on coordination: Finally, time compression may hinder the development of effective coordination routines, which is the third component of the learning curve.

Research in social psychology has shown that time pressure leads to poor group outcomes due to inadequate communication, including failure to share knowledge and adherence to poor decision-making schemes, such as dictatorial processes and the tendency to follow initial hunches rather than engaging in deliberate information processing (Karau & Kelly, 1992; Kelly & Loving, 2004; Isenberg, 1981). This suggests that individuals who are subjected to high levels of time compression in experience accumulation may not be able to work together productively. They are less likely to share ideas and incorporate them into best practices, resulting in poor outcomes.

In sum, time compression in experience accumulation negatively affects all three micro-processes that make up the firm's learning curve. Thus, taking more time to accumulate experience likely improves firm-level outcomes. Synthesizing these arguments, we suggest that:

H1: *Experience accumulation time positively moderates the relationship between the firm's cumulative experience and desirable performance outcomes.*

Note that we deliberately state a moderation hypothesis in order to expose the mechanism underlying TCD—that time compression in experience accumulation results in shallower learning curves—instead of simply stating that speed leads to poor outcomes, since the latter just demonstrates that TCD exists. However, we test for this latter proposition as well.

Interaction effect with complexity: We expect that the positive moderating effect of time taken to accumulate experience on the learning curve is likely to be exacerbated when the organization attempts to solve complex problems. Complex problems often involve more decision-making criteria that are also interdependent (Simon, 1991) and require greater levels of expertise to accomplish. Thus, individuals tend to need more complete mental models, and groups may need more deliberate coordination to solve the problems associated with complex tasks.

For example, in the IVF context, more complex patients tend to have less stable (more experimental) treatment plans. Older patients are likely to have no or few eggs, poorer quality embryos, poorer fertilization, and lower likelihood of embryo implantation. This implies the need for more steps, such as pre-implantation genetic diagnosis, ICSI injections (an invasive treatment procedure for fertilizing the eggs), and more experimental treatment trajectories requiring more attention. In general, treating more complex patients involves "longer checklists" and more intensive interaction between doctors, embryologists, and nurses (Stan & Vermeulen, 2013).

However, time compression in experience accumulation, as per the prior hypothesis, is likely to reduce learning, and thus the quality of capabilities developed. This is because time compression hampers the development of both individual mental models and coordination routines, both of which are more important in performing complex tasks. Thus, even though complex problems provide greater opportunities to learn (Haunschild & Sullivan, 2002; Mulotte, 2014; Rockart & Dutt, 2015), learning is less likely to be realized under time compression.

One of the key benefits of learning is the improvement of individual mental models. When individuals better understand cause-effect relationships, they are more likely to implement processes and procedures that improve outcomes. More complete mental models aid in executing more complex tasks that are not well understood, such as those relying on tacit knowledge and experiential learning (Pisano, 1994, 1996; Edmondson et al., 2003). Since time compression hampers mental model development, it makes it difficult to perform complex tasks.

In addition, time compression is likely to lead to greater difficulty in developing coordination routines, the lack of which especially compromises performance in more complex problems. As discussed earlier, groups are less likely to share information when constrained for time. Gruenfeld and Hollingshead (1993) argue that groups that achieve *integrative complexity* –

i.e., identify various dimensions of a problem and their interconnections - are better able to solve more complex problems. Gruenfeld, Hollingshead, and Fan (1995) found that only groups that had sufficient time to reflect on their experience achieved the required cognitive synthesis of information. Hinsz, Tindale, and Vollrath (1997) have suggested that groups that are subject to time compression are more likely to have a simpler and narrower perspective of the task, even more so than individuals acting alone. This narrower focus allows groups to act fast, but at the cost of less complete understanding of the problem. Since more complex problems are likely to have more interdependencies, poor coordination routines are even more injurious to the performance of firms handling more complex tasks. These arguments suggest that:

H2: The positive moderation effect of experience accumulation time on the relationship between the firm's cumulative experience and desirable performance outcomes is stronger when performing complex tasks relative to simpler ones.

Interaction effect with integration ability: Since the pioneering work by Lawrence and Lorsch (1967), it is widely recognized that an organization's ability to integrate differentiated activities greatly influences its performance. Integrating specialized routines into a coherent activity underlies much of the capability development that occurs in organizations (Dosi et al., 2000; Helfat & Winter, 2011). Several scholars have suggested that variation in coordination capacity can explain heterogeneity in learning curves (Pisano, Bohmer, & Edmondson, 2001; Reagans et al., 2005; Argote, 2012). As argued earlier, time compression is likely to lead to poor coordination in an organization, and thus poor outcomes arising from miscommunication, misunderstandings, and delays.

Organizations employ integrators in order to facilitate coordination between interdependent individuals (Mintzberg, 1979). Since they specialize in achieving coordination, integrators are more likely to spot opportunities to improve processes in ways that better align specialists' activities (Mohrman, 1993). Integrators likely improve the effects of learning by doing by spreading best practices (Valentine & Edmondson, 2014), and preventing specialists from having overly narrow mental models, thus enabling more systemic change (Hallen, Cohen, and Bingham 2020; Lapre and Van Wassenhove, 2001; Stan & Puranam, 2017). Thus, integrators aid in achieving stronger communication and coordination through knowledge codification and routinization, and these superior coordination routines result in steeper learning curves. Thus, the presence of integrators is likely to mitigate the negative moderating effect of time compression on the firm's learning curve. Based on these arguments, we hypothesize that:

H3: *The positive moderating effect of experience accumulation time on the relationship between the firm's cumulative experience and desirable performance outcomes is stronger when an integrator is not available.*

METHODS

Empirical Setting

The setting of fertility care is ideally suited to test our hypotheses. The in vitro fertilization (IVF) process consists of nine major stages, each of which contains multiple steps. Experts often specialize in a small number of these stages. Successful IVF treatment requires that these stages be executed with precise timing corresponding to the ovulation cycle, and the steps, stages, and timing are customized to an individual patient's physiology. For example, patients with a family or genetic history of specific diseases, or physiological conditions such as polycystic ovarian syndrome, require different treatment processes. Effective integration of clinical activities across these stages, tailored to patient requirements, is very important for successful IVF treatment.

An IVF treatment cycle for the female patient requires the joint participation of medical personnel in several areas of specialization, including gynecology, embryology, endocrinology, and nursing. It is important to note that the effectiveness of IVF treatment for a particular patient remains highly uncertain, with many 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 is also fairly prevalent in medicine (Cohen & Hilligoss, 2010; Solet, Norvell, Rutan, & Frankel, 2005). Therefore, during the time period of our study, IVF can be considered a fairly nascent field that provided significant opportunities for learning by doing. In light of the considerable demand for IVF treatment, clinics often face the choice between admitting additional patients at the risk of overburdening their staff vs. refusing new patients and foregoing additional revenue. Our data reveal a fair amount of heterogeneity in the number of patients treated by clinics.

Sample and Data

We obtained our data from the UK Human Fertilization and Embryology Authority (HFEA) records from 1992 to 2006. All fertility clinics in the UK are obligated to report the details of their operations to HFEA. Thus, our data capture the entire population of fertility clinics in the UK from the start of the industry. These features allow us to avoid the bias of left censoring and selection that hampers many learning-curve studies. Every year, clinics report operations data to HFEA, including the number of patients treated that year, patient outcomes, the general profile of patients, and technologies used. Due to regulatory changes, HFEA ceased collecting granular data for fertility clinics after 2006, limiting our observations to the 1992–2006 period. The unit of analysis is the IVF clinic-year; the total number of clinics with at least three consecutive years of performance data is 96, with a final sample of 1,097 clinic-years, although missing values reduced the effective sample size in many of our specifications.[1]

[1] We do not have three consecutive years of data for 22 clinics, which were therefore dropped from the analysis.

Dependent variables. We followed many studies in the learning-curve tradition that measure capability using operational metrics for performance such as cost or quality. In this vein, we measured clinic capabilities as the natural log of number of live-birth events (or successful treatments) for a clinic in a given year (Stan & Vermeulen, 2013). We controlled for the natural log of the total number of treatments (i.e., IVF cycles) administered in that clinic-year in the RHS. In alternative specifications, we used clinic success ratio—the number of live birth events divided by the number of treatments—as the outcome variable.

Independent variables**:** The learning curve suggests that high levels of experience lead to superior capabilities. In this paper, we argue that this relationship is steeper if such experience is built over a longer time period. We measured this relationship by interacting cumulative experience amassed by a firm with the firm's age in years, which is the time it took to accumulate that level of experience. We hypothesized that this interaction effect is positive. Given this hypothesis, the main effects of experience and time, without controlling for this interaction effect, may be positive or negative.

To measure *clinic cumulative experience* (Q_{it-1}), we followed the learning-curve tradition by cumulating all prior IVF cases that occurred since clinic *i* started offering IVF treatment until but not including the focal year (Epple, Argote, & Devadas, 1991; Stan & Vermeulen, 2013). We used the natural log as our independent variable in keeping with the learning-curve literature. *Firm age* (Age_{it-1}) is the number of years since clinic *i* started offering IVF treatment as reported to HFEA until but not including the focal year.

Task complexity: To test Hypothesis 2, we measured task complexity as the proportion of female patients above age 35 whom the clinic treated during the focal year, similar to Stan and

Vermeulen (2013).[2] Since the chance of success through IVF decreases sharply after the age of 35 (Sharif & Afnan, 2003, p. 484), treating older women represents a challenge for clinics. The greater salience of different specializations and the heightened need to coordinate among them means that cases involving older women are more complex.

Integrator: As argued above, achieving coordination among the multiple specialists poses a significant challenge in fertility treatment. In our data, some clinics had a defined *integrator* role fulfilled by either a nurse or a physician, who had the responsibility of shepherding a patient across the multiple specialists and ensuring transfer of all vital information about the patient across the several IVF treatment stages. To test Hypothesis 3, we specified the availability of integrators at each clinic: 0 if the clinic had no integrator role, representing a low level of coordination effort; and 1 if the clinic had an integrator (see also Stan & Puranam, 2017).[3]

Control variables: To control for the nature of the IVF *technology* used, following Stan and Vermeulen (2013), we specified the percentage of cycles utilizing a more invasive version of IVF during the year of observation (i.e., intra-cytoplasmic sperm injection). We used clinic fixed effects to control for unobservable characteristics of the clinic, and year fixed effects to control for time trends, such as increasing industry experience proxied by industry age and the regulatory shock of 2001 restricting the number of embryos that can be placed in patients (Stan & Puranam, 2017). We controlled for these particular measures in specifications without year fixed effects and obtained qualitatively similar results for our theory variables.

Estimation technique: Our empirical strategy followed well-established procedures for estimating the learning curve, allowing us to relate our findings to others and contribute to building

[2] We also used the number of older patients treated as a proxy; however, this measure is highly collinear with clinic volume, and therefore is less preferable. We thank an anonymous reviewer for suggesting this alternative.
[3] Surprisingly, this feature of organizational design displays very low within-clinic variation, with no instances of integrator adoption and only six clinics eliminating the employment of integrators within the observation window.

a cumulative body of knowledge. Using the formulation by Epple, et al (1991, p. 61),[4] the learning-curve estimation for clinic *i* at time *t* can be written as follows:

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

where A is a constant, Q_{it-1} is the clinic's accumulated experience until the focal year, λ is the clinic's learning rate (with respect to experience), and ϵ_{it} is the error term representing random factors affecting the treatment process. Since learning curves follow a power-law relationship, prior studies have and recast (1) as follows:

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

where B_{it} is the number of birth events for clinic *i* at year t[5], W_{it} is the number of treatments performed (alternately, the number of patients treated) in that year, *lnA* is the clinic fixed effect, (Epple et al., 1991). Following Darr et al. (1995) and Stan and Vermeulen (2013), we included the square term of volume ($W_{it}sq$,) to account for scale effects.[6]

Taking into account our theory on the effect of time on capabilities developed from experience accumulation, we treated the effect of time compression as an interaction effect of time with experience. Adding this term gave us the following equation:[7]

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

We predicted that β is positive (H1), and that it is larger for clinics treating more complex cases than for clinics treating simpler cases (H2) and larger for clinics that do not employ an integrator

[4] This basic estimation equation is used in multiple studies across disciplines, including in manufacturing (Argote, Beckman, & Epple, 1990), call centers (Kim et al., 2006), software (Boh et al., 2007; Narayanan et al., 2009), service operations (Darr et al., 1995; Staats & Gino, 2012), and healthcare (KC & Terweisch, 2011; Huckman & Pisano, 2006).
[5] Twenty-one observations had zero births, which we replaced with *ln* (0.01).
[6] Similar to these studies, we also used the square of the raw term (W_{it}) instead of lnW_{it} to reduce collinearity.
[7] This formulation of interaction effects to the learning curve is well accepted in this literature, including research considering the effect of complexity (Stan & Vermeulen, 2013), scope (Staats & Gino, 2012), and different dimensions of experience (KC et al., 2013).

than for clinics that do employ one (H3). We used an OLS regression with clinic fixed effects to estimate equation (3).

RESULTS

Table 1 shows the descriptive statistics, including mean, standard deviation, and minimum and maximum values for the variables of interest in our estimations. We found that adequate variation exists in the key independent and dependent variables. Table 2 shows the correlations between these variables. As expected, there is very high correlation between cumulative experience of the firm and firm age, which is the time in which this experience was accumulated. In addition, older firms also appear to treat more complex patients, perhaps because they are now more confident in their processes. When there is high correlation between independent variables, OLS estimates remain unbiased but become inefficient (i.e., standard errors are inflated), increasing the difficulty of finding statistically significant results (Gujarati, 2003: p349–50).

We utilized the binned scatter-plot technique (Starr & Goldfarb, 2020) to understand how speed influences capabilities. We plotted how clinic performance changes with speed of experience accumulation. We found an overall negative effect of speed on clinic performance. In addition, we found that speed has a more negative effect when (a) the clinic treats more complex cases and (b) for clinics that do not employ an integrator. These findings suggest support for our hypotheses, although they do not fully control for other effects.[8]

We next turned to the regression models to test our hypotheses. Model 1 in Table 3 shows the effect of the control variables. As expected, the number of treatments in any given year (lnW_{it}) strongly relates to number of births in the same year (lnB_{it}). Probing the negative coefficient for $W_{it}sq$, we observed diminishing returns to scale (we had only 9 out of 1,097 observations to the

[8] These plots are not included due to space constraints and are available in the online appendix.

right of the inflection point). The coefficient for proportion of complex patients is negative, but not significant, suggesting that not all clinics are unsuccessful in treating older patients.

In Model 2, we entered the main theory variables: experience, age, and their interaction. The interaction term between experience and age, β, in Equation 3, is positive and significant, supporting Hypothesis 1. In this model, we also noted that the effect of cumulative experience, λ, is not significant, which is unexpected, whereas the effect of time, α, is positive and significant. Since age and experience are highly collinear, this suggests the need to further probe these results.

To test the effect of complexity, we first split the sample at the median level of complexity into subsamples with lower and higher levels of complexity.[9] Model 3 and Model 4 test the effect of time compression on the low- and high-complexity subsamples, respectively. In Model 3, the interaction effect of experience and age is close to zero and not significant, whereas in Model 4 it is positive and significant. The coefficient of the interaction term in Model 4 is larger than in Model 3, as hypothesized. A contrast test suggests that the coefficients for the interaction terms across these models are significantly different [$F(1, 812) = 6.48$; p-val = 0.011], supporting H2.

To test the effect of an integrator, we split the sample into firms that do not employ an integrator (Model 5) and firms that do (Model 6). The interaction effect between experience and age is much larger for the no-integrator subsample relative to the integrator subsample. Once again, a contrast test shows that these coefficients are significantly different from each other [$F(1, 844) = 14.45$; p-val = 0.0002]. These findings support H3.

[9] We used the split-sample approach because interpreting three-way interaction effects is very difficult (Dawson & Richter, 2006; Jaccard & Turrissi, 2011). The split-sample approach may be inefficient, but it is unbiased since it does not constrain all the other variables from having the same effect across the subsamples (Wooldridge, 2006). Since Stan and Vermeulen (2013) have suggested that clinics shape their patient pools, the subsample approach appears to be more appropriate in this context.

We performed two key tests to probe these results. First, as noted earlier, older clinics have also treated more patients and thus have more experience. The VIF for Model 2 in Table 3 is 5.68 and ranges from 2.6 to 28.4 for the individual regressors. Some of these VIF values are above the acceptable value of 10 (Gujarati, 2003, p. 362). To remedy this issue, we adopted the orthogonal polynomial technique (Kleinbaum, Kupper, Muller, & Nizam, 1988; Sribney, 1995; for a recent application, see Billinger et al., 2021). Using this technique, we orthogonalized all regressors with a VIF >10 in the baseline model (Model 2 in Table 3). The results are shown in Table 4. The VIF for the orthogonalized model (Model 2, Table 4) is 1.66, with VIF for individual regressors varying between 1.1 and 4.7, well below the threshold value of 10. As Table 4 shows, all of our hypotheses are again supported. In addition, as Table 4 shows, the coefficient for learning from experience, λ, is positive across all models, whereas the coefficient for age, α, is positive and significant only in some models. Second, in the spirit of previous empirical work on TCD, we estimated how clinic outcomes change with *speed* of experience accumulation. Thus, we used the ratio of live birth events to the number of treatments (B_{it}/W_{it}) as the dependent variable and the speed of experience accumulation, measured as the ratio of cumulative experience to firm age (Q_{it-1}/Age_{it-1}), as the key independent variable. The results shown in Table 5 again support all our hypotheses.

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Robustness Checks

We performed a number of robustness checks on our results. These checks included alternative measures (tests 1–3), threats to causality (tests 4–5), alternative explanations (test 6), and confounding effects (tests 7 onward). Our results are largely robust to these different tests.

(1) We used an alternative measure of our dependent variable. In IVF treatment, singleton births are considered a high-quality outcome. Replacing our measure with this quality measure

results in qualitatively similar conclusions. (2) We used an alternative measure for our independent variable, wherein we measured experience by the number of patients treated rather than number of treatments (i.e., IVF cycles) performed. Once again, our results were qualitatively similar to what we found in our main specifications. (3) We measured complexity in two different ways, as suggested by Stan and Vermeulen (2013), i.e., the ratio of patients that failed to conceive in previous IVF treatments and the ratio of patients who have poor prognosis. Our complexity results were robust to these alternative measures.[10]

(4) We examined whether clinics that choose easier patients to work with have better outcomes and if that was driving our results. While this characteristic could affect overall success rates of the clinic, it remains unclear why this selection should matter for the interaction effect between age and accumulated experience, which is our theoretical contribution. However, we checked our main result in a subsample of NHS clinics. NHS is the UK's public health service, and by law, it may not turn away any patients who come to it for fertility treatment. In this sample, most women who received treatment in NHS clinics were referred by general practitioners where they are registered to clinics in their catchment areas; thus, selection was muted for the women and clinics. Our main result remains consistent in this subsample.

(5) We examined whether the quality of the clinic—potentially in regard to the skill level of doctors and other professionals—was 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, although the effect may be lower. Practically, our fixed-effects specification accounted for time-invariant clinic-level factors that influence the outcome. We tested for this possibility by including the quality achieved by the clinic in the previous year (Clinic Quality$_{t-1}$), measured as

[10] We thank an anonymous reviewer for suggesting this robustness check.

the ratio of live births to women treated, as an additional control in the regression. If clinic quality were driving our results, the previous year's quality should explain success rates for the current year, and cumulative experience and its interaction with time should not matter. In regressions using this control variable, although the previous year's quality was positive and significant, the results for our theory variables are qualitatively similar suggesting that our results are robust.

(6) We checked whether better-quality outcomes such as more live births occur at increased cost to the clinic. Since we do not have direct cost data for these clinics, we tested our results based on usage of a scarce and critical resource for fertility clinics. The fertility treatment process requires the creation of embryos and their manipulation, including their transfer from the petri dish to the patient. The micromanipulation of human gametes in the lab is a cost directly proportional to the number of embryos created. The use of more embryos means an increase in a clinics' costs both in accounting terms (i.e. more resources in terms of embryologist-hours, lab cultures and other consumables) but, more importantly, in terms of reputational costs (i.e., the use of more embryos per cycle increases the risk of multiple pregnancies which can lead to the loss of a clinic's license. Thus, we controlled for the total embryos transferred (as a cost) while examining the role of time compression on clinic outcomes. Our results remain robust.

(7) Finally, we checked for several confounding effects.[11] First, all of our specifications included year fixed effects to account for any time issues. We checked for specific explanatory variables that change with time, such as industry experience and the 2001 regulatory shock, by including them instead of year dummies. All of our results were robust. Second, it is plausible that employee turnover could present a challenge to clinics' ability to learn effectively. Since we did not have turnover data, we relied on a proxy to check this concern. We expected that turnover is

[11] We thank an anonymous reviewer for suggesting these additional checks.

more likely to pose a problem in clinics that are subject to high workloads and thus high stress for employees. Dividing the sample into above- vs. below-median load levels, we found a positive interaction between experience and age in both subsamples. Our sample is limited in some of the control variables we have available, such as size and learning capacity, which are only available between the years 1998–2006, as detailed in the methods section. We checked the robustness of our results in this subsample and found that our results are robust.

Finally, the clinic's choice to use an integrator is endogenous, with perhaps better-run clinics opting to employ one. From our data, we found that the choice to implement an integrator is time-invariant. Since integrator choice is time-invariant, it is reasonable to assume that the factors influencing that choice are also likely to be time-invariant. Since we ran specifications that include clinic fixed effects, we accounted for all time-invariant properties of the clinic, which somewhat mitigates this concern. As an additional robustness check, we used the coarsened exact matching (CEM) technique to match clinics that do vs. do not employ an integrator (Azoulay, Graf-Zivin, & Wang, 2010; Nandkumar & Srikanth, 2016), and replicated our analyses on this sub-sample. Our results remained robust. However, it is important to note that matching on observables mitigates but may not eliminate concerns of endogeneity. Due to space constraints, selected robustness checks are shown in the online appendix.

DISCUSSION

Understanding the isolating mechanisms that maintain firm-level heterogeneity is fundamental to strategy. While theoretically intuitive, one of the most important isolating mechanisms proposed, TCD, has so far received mixed empirical support, with some studies even showing "time-compression *economies*" in activities such as building plants (Hawk & Pacheco-de-Almeida, 2018). In addition, prior studies have not examined *why* TCD exists, and thus they do not tell us when TCD effects may be high or low. Our study throws light on these questions.

Learning by doing represents one of the primary ways in which organizations develop capabilities, and we show that increasing the time taken to accumulate experience positively moderates the effect of such experience on outcomes. Thus, our work showcases one of the micro-mechanisms that underlies TCD: Faster experience accumulation leads to shallower learning curves or a slower rate of capability development, answering a call for more work on the micro-mechanisms that underlie strategic concepts (Teece, 2007; Winter, 2012).

Clinics that accumulate experience in a short period of time perform poorly in comparison with firms that accumulate the same level of experience over a longer time period, we found. In our estimation, when cumulative experience doubles (from the mean), the number of live births increases by about 0.3percent; when this increase is accomplished by a firm that is one standard deviation (about four years) older than the mean (about seven years), the number of live births increases by about 1.6percent. To put these numbers in perspective, clinics that take more time to double their volumes are about 381 percent more effective in fertility treatment than clinics that do not take more time to ramp up experience. Figure 1 plots these effects.

----- INSERT FIGURE 1 ABOUT HERE ----------

We also found this time-compression effect to be exacerbated for clinics that treat more complex conditions. In our data, in clinics that predominantly treat simple cases, clinics that take one standard deviation more time to double their cumulative volumes see a 56% increase in the number of live births than those that do not take this extra time. For clinics that treat mainly more complex cases, taking more time to double their volume increases their effectiveness by 80%.

Further, we found interesting effects on clinic outcomes from the presence vs. absence of an integrator. More specifically, we saw that clinics without integrators perform much better only when sufficient time is allowed for internalizing the lessons gained from experience. In our data, for clinics that *do* employ an integrator, clinics that take four more years than the mean (seven years) to double their cumulative experience are about 6% more effective. In contrast, for clinics that *do not* employ an integrator, taking four more years than the mean to double their experience leads them to become 166% more effective. This finding suggests that coordination capability—an important constituent of firm capabilities (Dosi et al., 2000)—develops only with time, unless investments are made specifically to improve coordination. Specific investments in integrating differentiated activities (Lawrence & Lorsch, 1967) can speed up this process compared to just learning by doing, and they can thus improve the rate of capability development.

These results together illuminate important contingent effects under which the influence of time compression on capability development may be higher or lower, and they may help us to better understand conflicting results from prior empirical work. Overall, our empirical analyses show that the key drivers of TCD include experiential learning and achieving coordination, two important aspects of capability building (Helfat & Peteraf, 2003, 2015). Comparing the relative effect sizes suggests that according to our data, disruption in coordination ability is about twice as important as disruption to developing mental models.

The analysis so far underscores how TCD negatively influences the *rate* of capability development but does not tell us much about the final *level* of capabilities developed. Rockart and Dutt (2015) provide a rich discussion of the distinction between rates and levels, arguing that only differences in the steady-state levels of capabilities lead to sustained competitive advantage. Thus, to the extent firms have a higher capability development or learning rate, but ultimately the same level of capability, competitive advantage is only temporary. We utilized the method suggested by Rockart and Dutt (2015) to estimate whether faster firms' level of ultimate capability differed from that of slower firms. Our results suggest that there is no difference in the ultimate capabilities developed by faster vs. slower firms, although their learning rates differ significantly. Thus, our results suggest that in our context, TCD only results in a temporary (dis)competitive advantage arising from a slower capability development rate.[12]

In light of these findings, our work 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 primarily focused on its existence and influence on competitive advantage. For example, Fine (1998) speaks of industry clock-speed and its effect on competition in the industry. Koeva (2000) and Hawk and Pacheco-de-Almeida (2018) document differences in the time used to build new plants. However, these studies did not examine the factors that influence whether TCD is high or low. Although prior work has documented speed as a capability (Hawk et al, 2013), it has not explicitly considered the origin of this capability. We found that depending on the types of tasks and the coordination ability of firms, organizations within the same industry may be subject to higher or lower levels of TCD. Thus, our theory suggests that TCD is more likely to pose a problem when both individual learning and group coordination influence firm performance.

Limitations and future directions for research: Our results allow us to speculate about the conditions under which the TCD effect is likely to be larger vs. smaller. A fundamental condition that makes TCD relevant is experiential learning. Whenever experiential learning has a greater

[12] Currently there is no theory that suggests under what conditions TCD may lead to sustained vs. temporary competitive advantage, and no empirical paper measures this, with the exception of the work of Knott et al. (2003), who also found that TCD leads to a temporary competitive advantage in the pharmaceutical industry. Since these results are context-specific, with no theory to guide them, we present them here instead of in the theory and results section. This is in contrast to our findings about learning rates, where we are able to generate theoretically driven predictions. We thank an anonymous reviewer for this suggestion. These results are shown in the online appendix.

role, TCD can potentially become a core concern. For example, if the new capability developed is an incremental innovation, for an imitator or late entrant, TCD may not hold significance. On the other hand, if the innovation constitutes a significant leap above existing knowledge, it may prove more difficult for an entrant to catch up to the incumbent. This finding aligns with the work of Edmondson et al. (2003), who showed that innovations relying more strongly on tacit knowledge that is more difficult to transfer are typically less easy to imitate.

However, our theory adds a further nuance, based on whether a new development is a modular or component innovation vs. a more systemic innovation. A component innovation, regardless of its importance, can potentially be copied more readily—for example, by hiring experts. In contrast, with systemic innovations, coordination ability also plays a vital role. We suggest that innovations that are both systemic and a significant improvement over prior ones are likely to provide a longer-term advantage, from a TCD viewpoint. This idea presents a different mechanism for explaining why business model innovations such as the Toyota Production System are more sustainable, while TCD holds less importance in the pharmaceutical industry, as shown by Knott et al. (2003). In short, developing theory on moderators that determine whether TCD leads to temporary vs. sustainable advantage is a promising direction for future research.

Learning theories also have implications for how we think about firm adaptation. Prior theories of adaptation have mainly focused on the imperative for the organization to change as dictated by (frequently turbulent) environments. However, adaptation and fast-paced change could be generated internally, for strategic purposes, such as adherence to time-pacing (Eisenhardt & Brown, 1998), first-mover advantages, or the need to imitate quickly. However, these responses are likely to impair managers' cognitive abilities, as discussed. Empirical and modeling work on this question could lend a promising direction for future research.

Finally, our work has implications for long-term vs. short-term tradeoffs in firm strategy. Prior work has suggested that firms often embark on strategies that fulfill short-term goals, such as increased profits, at the expense of long-term goals such as survival. A particularly interesting point is how firms should make decisions about developing complex capabilities. Some studies have shown that firms learn more from solving more complex problems (Haunschild & Sullivan, 2002; Rockart & Dutt, 2015; Stan & Vermeulen, 2013). Our results suggest that faster firms are less likely to perform complex tasks effectively, and indicative analyses suggest that speed especially hampers learning from complex tasks. Understanding these interactions over time is an excellent avenue for future research.[13]

As with all research, ours is subject to some limitations. First, it used data from a single industry, which potentially limits generalizability. While the theoretical mechanisms at play are likely to be robust, we do not know whether context influences the importance of time compression and its moderators to performance outcomes. An alternative mechanism that may potentially explain some of our findings in this setting is that the physicians and staff may experience greater turnover under time pressure, and thus less learning. Our conversations in the field have broadly indicated that there may not be a strong relationship between time compression and turnover. We also have not systematically studied the effects of (dis)economies of scale or scope in our chosen setting. All of our models account for a clinic's capacity at time *t* and its square as a measure for scale, as prior work has done (Darr et al., 1995; Epple et al., 1991). In addition, we controlled for different combinations of complex vs. simple patients and did not find any nonlinear effects. Further, our study's outcome is a quality measure that may be less likely to be influenced by scale than the cost-based productivity measures that prior work has typically used. However, a more

[13] We thank an anonymous referee for suggesting these competing possibilities.

systematic study of economies of scale may prove useful. Additionally, whether an inflection point could occur in the relationship between time and capability development—i.e., whether the time taken may be too long for optimal accumulation of learning—is another pertinent issue. We approached this issue by estimating slopes for different speed deciles as well as using spline regressions with quintiles as knot points. In our data, the effect of speed appears to be monotonic. However, this may be context-dependent and merits further study in other contexts.

Further, the relationship between handling complex cases and capability building is not straightforward. An interesting extension of this study would be to conceptualize an optimal path that maximizes capability development. Our study has revealed the tradeoff between time taken and capability developed under different conditions of complexity and integration. Our data also suggest that complexity may pose a bigger challenge in the absence of integration. Thus, it is plausible that an optimal path would involve, for example, starting with relatively more modularity (low complexity) and greater speed, and then introducing more complexity later. Future research may explore nonlinear paths and tradeoffs among the three key components of TCD (time, complexity, and integration) explored here.

Another extension of our study could juxtapose the resource-based perspective with the Porterian tradeoffs-based perspective. It may prove fascinating to estimate the frontiers involving different dimensions of performance over time (the most obvious one being the cost-quality efficiency frontier) and how different firms push toward them, catch up, and fall behind, along with the consistency of the directions in which they go over time (e.g., improving mainly on quality vs. mainly on cost). We were not able to conduct such analysis in this study, due to data limitations. However, using data on two performance metrics—birth outcomes and wasted embryos—we did find that under certain conditions, clinics are able to achieve better outcomes within one or both of these dimensions. Clinics with integrators and clinics with more complex cases are less likely to waste embryos, for example, when they are not subject to TCD.

It is also interesting and pertinent to consider the perspective on resource redeployment and intertemporal economies of scope (Anand & Singh, 1997; Helfat & Eisenhardt, 2004; Kaul, 2011; Wu, 2013) since it also addresses issues related to time. Even though in such a case the resources are redeployed, the capability needs to be developed with appropriate new routines. An intriguing question is whether the clock gets reset, or if the firm can benefit from prior experience without suffering much from new TCD. The likely answer is that the modular resources themselves may not be subject to new TCD, but the routines interconnecting these resources have to be developed from scratch and are subject to much greater TCD (Chen, Kaul, & Wu, 2019).

Despite the aforementioned limitations, our work has some important strengths—namely, it is the first study that we know of that investigates the effect of the speed of experience accumulation on organizational learning curves. We also investigate contingent effects that occur when time-compression effects are mitigated vs. when they loom larger. Our estimations are robust to a variety of checks, including controlling for prior quality of the clinic, employing a cost measure in terms of embryos used, and predicting alternative dependent variables denoting high-quality capabilities, such as singleton births. Thus, this is one of the first studies that empirically investigates time-compression effects in a knowledge-intensive service-based setting.

CONCLUSIONS

In this paper, we have investigated the effect of time compression in experience accumulation on the operating performance of fertility clinics in the UK. We found that taking more time to accumulate a given level of experience is associated with better operational outcomes. We also found that (a) this effect is exacerbated for clinics that treat more complex cases, and (b) the effect is mitigated for clinics that employ an integrator to facilitate coordination among specialists. In our data, firms that accumulate experience quickly have a lower rate of capability development, but speed does not appear to influence the final level of capabilities. In other words, in our data, TCD results in only a temporary competitive disadvantage.

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Table 1: Descriptive statistics

Variable	Description	Obs	Mean	Std. Dev.	Min	Max
Live birth events (B_{it})	Number of live birth events at clinic i in year t. We use the natural log in regressions	1,039	71.60	69.31	0	512
Clinic Cumulative experience (Q_{it-1})	Cumulative experience of clinic i until year t-1. We use the natural log in regressions	1,052	1816.01	2297.09	0	13071
Clinic Age (Age_{it-1})	Clinic Age starting at year of first reported IVF treatment to HFEA until year t-1	1,097	7.17	4.40	1	14
Number of treatments (W_{it})	Number of treatments administered at clinic i in year t. We use the natural log in regressions	1,097	297.69	252.18	1	1467
Complex $Ratio_{it}$	Ratio of complex patients treated by clinic i in year t	1,097	0.46	0.10	0	0.84
ICSI Tech Use_{it}	Percentage of treatment cycles using ICSI technology at clinic i in year t	1,040	0.21	0.22	0	0.79
$Integrator_i$	Dummy variable indicating whether clinic i utilized an integrator (this is time invariant in our data)	998	0.49	0.51	0	1

Table 2: Correlation table

		1	2	3	4	5	6	7
1	ln(live birth events: B_{it})	1						
2	ln(clinic cum exp: Q_{it-1})	0.49	1					
3	Clinic Age_{it-1}	0.37	0.74	1				
4	Ln(num of treatments: W_{it})	0.90	0.55	0.42	1			
5	Complex $Ratio_{it}$	0.25	0.27	0.38	0.25	1		
6	ICSI Tech Use_{it}	0.30	0.38	0.59	0.24	0.41	1	
7	$Integrator_i$	-0.03[a]	-0.04[a]	-0.02[a]	-0.09	0.12	-0.002[a]	1

Notes: All correlation values except those denoted with 'a' are significant at 95%. In our data presence of an integrator varies only by clinic but not by year.

Table 3: Predicting ln(live birth events: B_{it}) – OLS fixed effects regression

VARIABLES	(1) controls	(2) interact	(3) Lo Complex	(4) Hi Complex	(5) No Integrator	(6) Integrator
ln(clinic cum exp: Q_{it-1})		-0.023	-0.202	0.222	0.180	-0.124
		(0.116)	(0.149)	(0.184)	(0.173)	(0.111)
		[0.844]	[0.174]	[0.230]	[0.299]	[0.267]
Clinic Age_{it-1}		0.176	0.247	0.081	0.126	0.238
		(0.104)	(0.131)	(0.166)	(0.165)	(0.097)
		[0.093]	[0.059]	[0.626]	[0.444]	[0.015]
$lnQ_{it-1}*Age_{it-1}$		0.111	-0.033	0.178	0.338	-0.052
		(0.061)	(0.083)	(0.099)	(0.090)	(0.059)
		[0.071]	[0.687]	[0.073]	[0.000]	[0.377]
ln(num of treatments: W_{it})	1.591	1.698	1.613	1.567	1.948	1.443
	(0.038)	(0.044)	(0.057)	(0.080)	(0.068)	(0.050)
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
(num of treatments: $W_{it})^2$	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
	[0.000]	[0.000]	[0.001]	[0.011]	[0.000]	[0.000]
Complex $Ratio_{it}$	-0.367	-0.351	-0.331	-0.986	-0.966	-0.389
	(0.286)	(0.285)	(0.412)	(0.596)	(0.430)	(0.291)
	[0.199]	[0.218]	[0.423]	[0.099]	[0.025]	[0.181]
ICSI Tech Use_{it}	0.009	-0.112	0.265	-1.022	-0.097	-0.248
	(0.222)	(0.226)	(0.290)	(0.336)	(0.314)	(0.218)
	[0.969]	[0.621]	[0.363]	[0.003]	[0.758]	[0.256]
Constant	-4.728	-5.408	-5.053	-3.945	-6.891	-3.637
	(0.213)	(0.284)	(0.330)	(0.613)	(0.455)	(0.326)
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Year FE	Y	Y	Y	Y	Y	Y
Clinic FE	Y	Y	Y	Y	Y	Y
Observations	1,039	1,025	689	336	485	463
R-squared	0.719	0.725	0.722	0.729	0.770	0.823
Number of clinic	96	95	86	76	40	41

Standard errors in parentheses; p-vals in brackets. Contrast indicating difference in coefficient of the interaction term across low versus high complex sub-samples: F(1, 812) = 6.48, p-val = 0.011; across integrator present versus absent sub-samples F(1, 844) = 14.45, pval = 0.0002. lnQ and Age are standardized before interacting. All models include specified number of clinic fixed effects and 14 year fixed effects. Given the high correlations, we checked the VIF values: for model 2, VIF value is 5.68, and range from 2.62 to 28.4 for individual regressors.

Table 4: Predicting ln(live birth events: B_{it}) using orthogonal polynomials for the independent variables – OLS fixed effects regression

VARIABLES	(1) Interact	(2) Lo Complex	(3) Hi Complex	(4) No Integrator	(5) Integrator
Orthog ln(clinic cum exp: Q_{it-1})	0.970	0.890	1.012	1.109	0.878
	(0.040)	(0.055)	(0.073)	(0.056)	(0.039)
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Orthog Clinic Age_{it-1}	0.098	0.065	0.065	0.171	0.055
	(0.048)	(0.063)	(0.078)	(0.073)	(0.047)
	[0.042]	[0.299]	[0.405]	[0.020]	[0.244]
Orthog $lnQ_{it-1}*Age_{it-1}$	0.730	0.620	0.709	0.945	0.542
	(0.039)	(0.053)	(0.066)	(0.059)	(0.040)
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Orthog ln(num of treatments: W_{it})	1.292	1.227	1.186	1.477	1.097
	(0.033)	(0.043)	(0.062)	(0.052)	(0.038)
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
(num of treatments: $W_{it})^2$	-0.000	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
	[0.000]	[0.001]	[0.011]	[0.000]	[0.000]
Orthog Complex $Ratio_{it}$	-0.034	-0.032	-0.096	-0.094	-0.038
	(0.028)	(0.040)	(0.058)	(0.042)	(0.028)
	[0.218]	[0.423]	[0.099]	[0.025]	[0.181]
ICSI Tech Use_{it}	-0.112	0.265	-1.022	-0.097	-0.248
	(0.226)	(0.290)	(0.336)	(0.314)	(0.218)
	[0.621]	[0.363]	[0.003]	[0.758]	[0.256]
Constant	3.582	3.397	4.087	3.304	3.861
	(0.097)	(0.131)	(0.160)	(0.130)	(0.101)
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Year FE	Y	Y	Y	Y	Y
Clinic FE	Y	Y	Y	Y	Y
Observations	1,025	689	336	485	463
R-squared	0.725	0.722	0.729	0.770	0.823
Number of clinic	95	86	76	40	41

Standard errors in parentheses; p-vals in brackets. Contrast indicating difference in coefficient of the interaction term across low versus high complex sub-samples: $F(1, 908) = 6.20$, p-val = 0.013; across integrator present versus absent sub-samples $F(1, 847) = 9.18$, pval = 0.0025. All the variables whose VIF values were above 10 in the standard model (table 3, model 2) were orthogonalized and indicated here with the prefix orthog. All models include specified number of clinic fixed effects and 14 year fixed effects. VIF values for model 1 is 1.66, and range from 1.12 to 4.7 for individual regressors. VIF values are comparable to model 1 for all other models, and well below the critical value of 10.

Table 5: Predicting Success Rate (live birth events: B_{it}/number of treatments: W_{it}) using Speed of experience accumulation ($Speed_{it-1}$ = Clinic cumulative experience Q_{it-1}/Clinic Age_{it-1}) – OLS fixed effects regression

	(1)	(2)	(3)	(4)
VARIABLES			No Integrator	Integrator
ln($Speed_{it-1}$)	-0.015	-0.010[a]	-0.028	-0.010
	(0.003)	(0.007)	(0.006)	(0.005)
	[0.000]	[0.127]	[0.000]	[0.028]
Complex $Ratio_{it}$	-0.068	-0.004	-0.092	-0.065
	(0.019)	(0.077)	(0.032)	(0.028)
	[0.000]	[0.956]	[0.004]	[0.018]
ln($Speed_{it-1}$)* Complex $Ratio_{it}$		-0.012[a]		
		(0.014)		
		[0.392]		
ln(num of treatments: W_{it})	0.029	0.029	0.031	0.029
	(0.003)	(0.003)	(0.005)	(0.006)
	[0.000]	[0.000]	[0.000]	[0.000]
ICSI Tech Use_{it}	-0.023	-0.021	-0.016	-0.018
	(0.014)	(0.014)	(0.022)	(0.019)
	[0.108]	[0.135]	[0.459]	[0.342]
Constant	0.040	0.016	0.108	0.013
	(0.021)	(0.034)	(0.035)	(0.031)
	[0.056]	[0.629]	[0.002]	[0.670]
Year FE	Y	Y	Y	Y
Clinic FE	Y	Y	Y	Y
Observations	943	943	445	436
R-squared	0.403	0.403	0.375	0.480
Number of clinic	96	96	39	42

Standard errors in parentheses; p-vals in brackets. In model 2, these two coefficients indicated by 'a' are jointly significant: $F(2, 829) = 9.24$, p-val =0.0001. Contrast indicating difference in coefficient of the interaction term across integrator present versus absent sub-samples $F(1, 782) = 12.64$, pval = 0.0004. All models include specified number of clinic fixed effects and 14 year fixed effects.

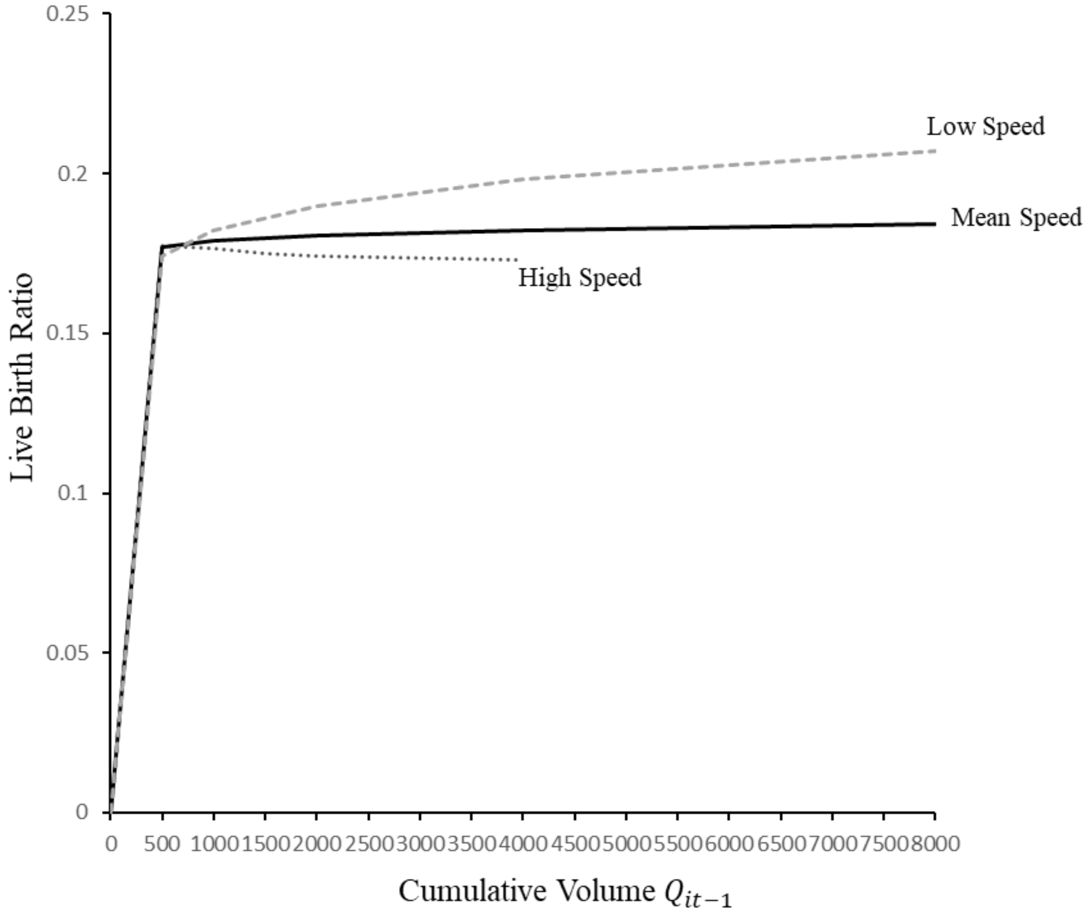

Figure 1: Joint effect of experience and firm age on clinic outcomes

Notes: The y-axis plots live births divided by the mean number of treatments in a given year (about 180 in our sample). The mean speed line plots the performance of firms with given level of cumulative volume (experience) at mean age (7 years in our sample). The high speed and low speed lines are for firm ages of 5 and 10 respectively, which is about 0.5 standard deviation from mean age in our sample. We plot the traditional learning curve with origin starting at zero experience and zero performance. In our data, firms with 5 years of age have not had a chance to accumulate more than about 4000 cases in prior experience, and thus the points to the right of the x-axis are missing. Firms at 7 years of age have a minimum of about 1000 cases in prior experience and at 10 years of age have a minimum of about 1200 cases in prior experience. Thus, although we plot the traditional learning curve, we should keep in mind that for older firms the lower experience points do not exist in the data and are extrapolated from the regression.