How Long Does It Take to "Get to" the Learning Curve?

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ABSTRACT

The learning curve describes learning from experience, even in its earliest phases, as an iterative process in which the ratio of positive to negative outcomes rises sharply with experience before becoming subject to diminishing returns. In contrast, the organizational learning literature suggests that learning when experience is limited is difficult, and unfavorable outcomes are common. Resolution of these competing claims is especially important in the context of strategic decision-making, where the costs of unreliable learning are significant. We develop theory and draw on a unique dataset of strategic decisions – the selection of franchisee applicants by a large global remittances firm over a 14-year period – to test competing predictions about how long it takes to "get to" the learning curve: that is, to the point after which performance trends reliably positive. Results from 3,620 selection decisions in 165 markets indicate that it took this organization about 19 decisions to reach the learning curve. Further, we identify factors that reduce the *cost* of reaching the learning curve, as well as the *number* of decisions required to reach it. Implications for organizational learning theory in general and strategic decision-making in particular are explored.

Keywords: experience-based learning; information processing; strategic decision-making

A key premise of the organizational learning literature is that experience teaches firms lessons that help them improve (Cyert & March, 1963; March & Simon, 1958). This conjecture is incorporated in many organizational learning theories (Argote & Miron-Spektor, 2011) and is reflected in one of the most widely used learning models – the traditional learning (or experience) curve model (Lieberman, 1987; Yelle, 1979). It proposes that organizational outcomes improve with experience, rising sharply through its initial accumulation phases before becoming subject to diminishing returns. A wealth of studies provide support to these predictions across a wide range of contexts and outcomes – from hotel management (Baum & Ingram, 1998) and nuclear power plant operations (Lester & McCabe, 1993) to cost-efficiency (Argote, Beckman, & Epple, 1990) and survival (Baum & Ingram, 1998). The positive experience-performance relationship has also been documented in a breadth of strategic contexts, including new product introductions (Nerkar & Roberts, 2004), acquisitions (Capron, Anand, & Mitchell, 2007), diversification (Barkema & Schijven, 2008), international expansion (Lu & Beamish, 2001), and strategic alliances (Anand & Khanna, 2000). While the organizational learning and strategic learning literatures associate the positive relationship between experience and performance with learning, they also tend to attribute the absence of that relationship to failed learning processes (Anand et al., 2016). Moreover, the prospect that differences in their attributes (e.g., the pace of experience accumulation), facilitate or inhibit learning has largely escaped scrutiny.

The lack of attention to the attributes of the learning experience is curious because the shape of the learning curve, especially in its initial phases, is a critical determinant of the costs and benefits of a strategic decision. Hence, generalizing learning models from contexts like manufacturing, where experience accumulation is continuous and performance feedback instantaneous, to strategic contexts where experience is episodic and performance feedback is ambiguous, leaves important questions unanswered (Anand et al., 2016). Such questions include how much experience is needed before reliable learning can occur, and how do differences in the nature of those experiences shape outcomes? Knowledge about how much is critical because limited experience not only complicates learning, but also significantly increases the risks of type I (false positive) and type II (false negative) error (Dahlin, Chuang, & Roulet, 2018). Knowledge about contextual differences is crucial because the ability to transfer knowledge from prior experiences, or to learn by observing others (i.e., vicarious learning), is prone to error due to information asymmetries (Denrell, 2003), and selection errors (attempting to learn from incommensurate experiences, as well as the failure to recognize novelty; Anand et al., 2015). To date, however, these questions have largely escaped scrutiny by strategy researchers.

In this study, we focus our attention on the early phases of the experience accumulation process and explore how long it takes (that is, *how much experience must accumulate*) to reach the positive portion of learning curve; that is, the point after which learning outcomes, when plotted, trend reliably positive. We draw on the organizational learning, learning from failure, and the strategic learning literatures to develop theory about the challenge of learning when experience is limited. We test our conjectures by drawing from a dataset of franchisee application-approval decisions made by a global remittances firm over a 14-year period (2001-2015) while constructing a European money transfer network that spans 14 nations. Over this time period, the firm entered over 600 new markets. Our data therefore contains information about the firm's initial learning experiences, as well as information about how franchisee selection improved over time. After screening the data, the final sample included 3,620 franchisee decisions from 165 remittance markets (e.g., the market for remittances from Madrid to Pakistan).

Out dataset is uniquely suited to explore our research questions because it allows us to observe a large number of relatively homogeneous strategic decisions over time, and across a large number of settings. Doing so also allows us to examine how differences in particular attributes of the decision, such as their pace of accumulation or the amount of variance in performance, shapes the journey to the learning curve. Data about the factors that accelerate the race to the positive phase of the learning curve, and/or make it less costly, allow us to explore questions that have significant practical implications for the decision-makers.

The results from analysis of those 165 intra-organizational learning curves indicate that the experience-performance relationship is U-shaped. That is, it is characterized by negative learning outcomes in its earliest phase, and then trends positive once sufficient experience has accumulated. Moreover, once the inflection or turning point is reached, our curves from that point forward resemble the traditional learning curve. Interestingly, we also observe that the mean inflection point (i.e. the point where the negative trend in experience outcomes becomes positive) is 19 decisions – a number that is quite large in the context of strategic decision-making.

Further, we identify attributes of the learning experience that reduce the cost of reaching the learning curve[1] (that is, those attributes are associated with increased revenue, and thus shift the u-shaped curve up), as well as the number of decisions required to reach it (that is, it shifts the turning point of the u-shaped curve to the left). Our data suggest that the firm selected higher performing franchisees in markets where the average interval between application decisions was

[1] We infer increased revenue reduces the cost of learning. Unfortunately, our dataset does not contain any information about the cost of delivering these services.

about a month, and poor performing franchisees in markets where the decisions were approved in less than 10 day intervals. Results indicate these learning effects are economically important – the difference between high and low performing franchisees exceeds 500 euro per day, or 12% to 20% of average initial franchise revenue. And while our data suggest that learning is less costly when outcome variance (that is, variance in franchise revenues) is high, greater variance does not speed learning: The journey to the learning curve is about the same in both high and low variance groups (17 and 21 decisions, respectively).

This study contributes to our understanding about learning in the strategic decision-making context (Hough & White, 2003; Hutzschenreuter & Kleindienst, 2006; Bingham & Eisenhardt, 2011). To date, the strategy literature on learning has assumed that there is a positive relationship between experience and performance (Anand et al, 2016). However, we have yet to explore *how much* experience is required before learning (as indicated by improved outcomes) occurs. Further, shedding light on behavior during the initial phases of the learning curve brings to light a missing piece of the organizational learning puzzle and helps bridge the gap between that literature and the strategic decision-making context, a setting characterized by ambiguity and limited experience.

Finally, by explaining the differentiated effects of the conditions in which experience is acquired and applied, our work helps to advance the debate about how and when experience might be a good or a bad teacher (Argote, McEvily, & Reagans, 2003; Kim, Kim, & Miner, 2009). Moreover, our work also generates insight about how the strategic decision context influences how effectively firms learn or apply what they have learned, and raises important questions about the limits of the learning curve in strategic environments, in particular, those with few events. We begin with a review of theory and the development of our hypotheses.

THEORY

The organizational learning curve (also referred to as the "experience curve") proposes that organizational outcomes improve with experience, having greatest momentum at the early stages and declining rates of improvement at latter stages of experience accumulation. The learning curve was generalized from its original applications in manufacturing (Yelle, 1979), and became widely used to forecast how cumulative experience affects performance in a variety of organizational contexts, including; new product introductions (Anand et al, 2016), international expansion decisions (Barkema, Bell, & Pennings, 1996; Shaver, Mitchell, & Yeung, 1997), diversification moves (Pennings, Barkema, & Douma, 1994), alliance-formation (Anand & Khanna, 2000), corporate acquisitions (Barkema & Schijven, 2008), stock market responses (Anand & Khanna, 2000), and more. (See Lapré and Nembhard (2011) for an overview).

While learning curves have been observed in a variety of settings, the utility of generalizing the concept across decision contexts varies with attributes of the activity itself. In settings characterized by continuous production and learning by doing, traditional learning curves (strong initial positive effects followed by diminishing positive effects) are often observed. In these settings, the organizational learning literature suggests information from earlier or similar failure events can be quantified and contrasted with successful events, and lead to ongoing process improvements and reduced failure rates; e.g., Total Quality Management or TQM (Lapre, Mukherhee & Van Wassenove, 2000).

However, learning in contexts where production is complex, such as medical procedures, is characterized by knowledge-based or analytical learning (Dahlin et al., 2018). The reduction of error in knowledge-based learning requires information about the nature of the event itself, information about properties of the factors and processes involved, and careful analysis of causal relationships (Zhao & Olivara, 2006). Research has established that the learning process is shaped by some attributes of the event itself, like the magnitude of failure (Madsen, 2009), the pace of the event (Edmondson et al., 2001), the visibility of the event, (Desai, 2011), and recency (Haunschild, Polidoro Jr, & Chandler, 2015). In the main, organizations learn more from failure than from success (Baum & Dahlin, 2007), and learn faster when events are frequent (Edmundson et al, 2001), and variable (Desai, 2011). Recency increases the salience and motivation for learning (Haunschild et al., 2015). However, while more is usually better, high event frequency can lead to information overload and limit learning (Dahlin & Roulet, 2014; Hayward, 2002), especially when organizations do not have sufficient time to reflect and process information (Kerr, 2009).

Recently, the organizational learning literature, and, in particular, the growing stream of research about learning from failure, has paid increased attention to the risks of learning when experience is limited. For example, Dahlin et al. (2018) note that limited experience significantly increases the risk of type I (false negative) and type II (false positive) error. They note that learning from success or failure is possible if organizations have an accurate understanding of causality and process implementation. However, when cases are few and the organizations' understanding of causality or process implementation is faulty or incomplete, the risk that success or failure is spurious poses a significant risk to learning. Spurious success is problematic because the absence of negative effects reduces the motivation to learn from potential or near failures (Zhao & Olivera, 2006). It also reduces the incentive to document them (thereby increasing the risk of what Ramanujam (2003) calls latent error), while reducing the ability to diagnose them (Dahlin et al., 2018). Spurious failure is problematic because it can lead to misattribution, and/or the replacement or modification of potentially reliable routines.

Complexity and ambiguity further increase the threat of spurious success or failure to effective learning (Dahlin et al., 2018).

To date, however, questions about the amount of experience required to support learning has largely escaped scrutiny from strategists.[2] While some strategy research (mostly on M&A and strategic alliances) features samples in which firms' experience was sufficiently large to limit the risk of spurious success or failure,[3] the preponderance of studies rely on samples in which firm experience is limited. For example, March, Sproull and Tamuz (1991) describe a variety of methods that organizations use to learn from samples of one or fewer and Bingham (2009) suggests firms can learn from as few as five experiences with international expansion.[4] Meanwhile, Trichterborn, Knyphausen-Aufseß and Schweizer (2016) conclude a dedicated M&A function can improve organizational learning but rely on a sample in which 65% made fewer than 5 acquisitions and only 15% of the sample made more than 10 acquisitions. In contrast, Anand et al. (2016) concludes that little learning occurred using a product development sample in which the mean level of experience was 2.75. The range of experience in their study was also right censored: Only 25% of the sample introduced more than 3 new products and only 11% of the firms introduced more than 6 new products. In contrast, in our study the mean level of experience is 24 and the average number of experiences required to achieve reliable performance is 19.

In other strategy studies, learning was inferred from relatively heterogeneous and/or episodic cases. Madsen and Desai (2010) find evidence of both first-hand and vicarious learning

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[2] The exception is Laamanen & Keil (2008), which explores serial acquirer behavior.
[3] For example, average experience in Zollo & Singh (2004) was 12.4, 20.8 in Kale and Singh (2007), and 9 in Laamanen & Keil (2008).
[4] Curiously, despite his claim that firms in his sample achieved success over time, table 2 of his study (Bingham, 2009: 327) indicates that only one of the nine firms studied achieved higher performance after five experiences with international expansion. In all other cases, performance was about the same or worse than the performance of their first entry.

in a sample of 4,663 launches of orbital space vehicles made by 30 organizations from 9 nations over a 38-year period. Anand et a.l (2016) studied 437 new jet aircraft projects over a 56-year period undertaken by 159 firms and Zheng, Miner, and George (2013) present evidence of individual and group-level experiential learning in a study of 778 patent license agreements executed by a major university over an 18-year period. Another factor that limits inference in these, and many other studies, is that they rely on a dichotomous dependent variable; e.g., success or failure. This makes inferences about the relationship between experience and how much learning occurred difficult. In contrast, the strategic decisions we study are homogenous, made by the same organization across a variety of markets, and decision outcomes are evaluated using a continuous measure of performance (revenue).

Differences in the strategic learning literature with respect to the number of experiences, the timing of those experiences, and their performance, limits our ability to reliably describe the experience-performance relationship. Absent information about what happens when organizations make repeated strategic decisions across a variety of settings, we simply do not know how change in attributes like their number, pace, and variance in the prior decisions' outcomes shape the strategic experience - performance relationship.

We explore these questions by developing theory about the impact of various attributes on the experience-performance relationship, and then test our conjectures using a large unique dataset of strategic decisions made by a global remittances firm over a 14-year period. The decision we study (the award of franchises to applicants) is appropriately classified as a strategic decision: Such decisions are largely irreversible, involve significant opportunity costs, and are shaped by both environmental and competitive conditions. That is to say, efforts to establish a market presence are motivated by strategic considerations like exogenous growth in the target market (e.g., rising immigration from a specific nation) or the entry of competitors into specific regional or national markets. Moreover, the selection of franchisee candidates is shaped by strategic considerations because the target markets are highly localized (i.e., franchises are awarded in specific geographic locations) and best served by a specific type of applicant (e.g., those who have the requisite skills *and* match the ethnic or national heritage of the target remittance market; e.g., Hindi or Buddhist, Pakistani or Malaysian). Moreover, franchises can only be revoked after a sustained period of poor performance. Thus, poor performing franchises create significant opportunity costs for the firm. As a result, our study is comprised of a very large sample of repeated strategic decisions that is well suited for exploring how variance in decision attributes across markets shapes strategic outcomes.

HYPOTHESES

Learning to make good decisions requires monitoring past outcomes (Cyert & March, 1963; Huber, 1991; March et al., 1991). Yet, until a sufficient volume of decisions have been made, experience is not a reliable guide. Questions about how much experience is required to support learning in strategic decision-making contexts are especially pertinent because, at the earliest stages of strategic learning, strategic decision-makers must learn from samples of fewer than one (March et al., 1991) or, as Pisano (1996:1097) puts it, 'before they start doing.' The strategic decision-making literature describes a variety of methods and techniques that organizations use to learn before they start doing, including transferring knowledge from other contexts (Anand et al., 2015), learning through observation or vicarious learning (Argote & Miron-Spektor, 2011; Ke, Staats, & Gino, 2013), theorizing around hypothetical cases (March et al., 1991), drawing on analogies (Gavetti, 2005; Gavetti, Levinthal, & Rivkin, 2005; Kraatz, 1998), and simulations (Argote & Miron-Spektor, 2011).

While the lack of prior experience imposes constraints (Catino & Patriotta, 2013; Risen, Gilovich, Sternberg, Halpern, & Roediger, 2007), the strategic decision-making literature asserts that learning from small samples can provide substantial advantages (Maitland & Sammartino, 2015). Specifically, in the absence of experience, decision-makers are forced to simplify reality (Christianson, Farkas, Sutcliffe, & Weick, 2009; Zollo, 2009), use intuition and rely on heuristics (Bingham & Eisenhardt, 2011), and focus on the most critical facts. Often, they do so by focusing on impactful events and especially on those that have metaphorical power (March et al., 1991). A focus on simplified metaphorically powerful narratives is viewed as enabling organizations to build rich stories that help them better understand the mechanics of a process and gain insight about the decisions might be reached (March, 2011; March et al., 1991). A focus on rich narratives also helps reduce the impact of noise, uncertainty, and ambiguity on decision-making (Dalhin et al,. 2018).

Despite these assertions, abundant evidence suggests that learning from limited experience is difficult. Efforts to integrate the indirect and direct effects of experience – that is, to merge theoretical and empirical knowledge (Argote & Miron-Spektor, 2011) – may result in substantial interpretability confusion, attribution error, false lessons, and superstitious learning (March et al., 1991). In the absence of sufficient experience, patterns in the data may have yet to emerge and/or are difficult to identify, which can confound inference. Data required for analysis may not yet exist in sufficient quantity to be reliable, or it may be missing because decision-makers do not yet fully understand causality and hence, are unaware of critical data requirements. Further, when experience is limited, decision-makers may not know the performance properties of a given decision context (e.g., a market or corporate activity) or how performance might change across settings. Put simply, decision-makers may not know whether performance is good or poor until sufficient experience has accumulated.

As a result, when experience is low, the decision-makers' ability to distill information and exercise judgment is limited. Decision-making when experience is low also involves significant cognitive burden as decision-makers are forced to continuously rework their assumptions about the environment and causality, to unlearn and to learn again (Hedberg, 1981). Limited experience also magnifies the consequences of spurious failure and success. Spurious failures increase ambiguity and may cause actors to incorrectly modify routines and processes (Dahlin et al, 2018). Meanwhile, spurious success can cause organizations to hold onto flawed beliefs (Kale, Dyer, & Singh, 2002), minimize the potential significance of "near misses" (Kim & Miner, 2007), or to attribute knowledge or decision-making errors to the violation of rules, incorrectly executed routines, flawed skills, or chance (Rerup, 2006; Zhao & Olivera, 2006). These conditions increase the likelihood of mistakes when experience is limited.

Other research suggests that the experience-performance relationship may trend negative when experience is limited (Finkelstein & Haleblian, 2002; Haleblian & Finkelstein, 1999). March (2011) notes that organizations replicate successful practices, a phenomenon he labels success replication bias. Doing so can be problematic. For example, Finkelstein and Haleblian (2002) contend that because subtle differences between experiences can greatly complicate knowledge acquisition and transfer, second experiences often have worse performance outcomes than first experiences. Similarly, Kim, Kim, and Miner (2009) argue that low levels of experience harm performance due to increased risk of inaccurate inferences and inappropriate generalizations. Further, when experience is limited, spurious failures or successes may exacerbate the risk of misattribution or cause the organization to retain ineffective practices or modify potentially effective routines (Dahlin et al, 2018), causing the negative experience-performance relationship to persist.

Finally, the experience – performance relationship may trend negative because decisions are drawn from a limited pool of options, which is bounded by current knowledge constraints. Since expectations of superior performance motivate the selection of options, it is likely that options will initially be picked in the order of decreasing quality. Performance might then decline until experience reveals knowledge that allows the organization to identify and select better options. But once sufficient experience has accumulated, patterns emerge, knowledge generated by experience acquires structure, and the cognitive load needed to make further decisions should decline. Put differently, as experience accumulates, the likelihood that the organization will make better decisions rises. Thus, a positive relationship between experience and learning (i.e., the traditional learning curve) may start to emerge after an initial period of failure and success, knowledge accumulation, and sense-making activities. We therefore anticipate that that the relationship between prior experience and repeated decision outcomes will follow a u-shape: That is, the curve will trend negative during initial stages of experience accumulation but rise thereafter. Accordingly, we posit:

> **H1*:*** *The relationship between accumulated experience and the outcome of subsequent strategic decisions is U-shaped, such that the relationship will trend negative at the low experience levels and become positive at high experience levels.*

The Role of Pace and Variance

Prior research emphasizes the importance of studying the attributes of the decision-making context to ensure a more realistic understanding of how organizational learning occurs (Argote &

Miron-Spektor, 2011; Glynn, Lant, & Milliken, 1994). In that literature, an important source of contextual differences lies in the attributes of decisions, and the way those attributes influence the manner in which information accumulates and can be utilized (Argote & Miron-Spektor, 2011; Laamanen & Keil, 2008). In this study, we focus on the temporal dimensions of the process of experience accumulation. Specifically, we examine how the pace of decision-making (as indicated by the average interval between decisions) and variance in the prior decision's outcome (as indicated by variance in franchisee revenues), interact with accumulated experience to shape the curvilinear experience-performance relationship.

Pace. One of the key attributes that shapes the learning process is pace (Laamanen & Keil, 2008; Nadolska & Barkema, 2007; Vermeulen & Barkema, 2002; Wally & Baum, 1994). Higher pace implies that information accumulates at a higher rate, which, all things being equal, may speed the journey to the learning curve. Higher pace is associated with greater recency, which increases the salience of the learning activity (Haunschild et al., 2015), and incentivizes the organization to engage in the codification of data about processes and performance (Bingham, Heimeriks, Schijven, & Gates, 2015). Codification facilitates the development of the organizational capabilities needed to manage process (Zollo & Winter, 2002).

However, higher pace also introduces limitations to the ability to process information and can have significant downsides when organizations face strategic decisions. First, increased pace reduces the time organizations have to process gather, evaluate, and reflect on gathered information. In knowledge-based learning, time for reflection rises in importance as the complexity of the activity rises (Dahlin et al., 2018). If the decision setting is new to the organization – as is often the case when facing strategic decisions – the organization may not yet understand how idiosyncratic environmental attributes, like market composition or geography, influence performance (Eisenhardt & Bingham, 2017). Pace increases the information burden (Laamanen & Keil, 2008), forcing the organization to identify the information needed for codification and capability development (Trichterborn et al, 2015). Data must accumulate before the influence of these factors can be identified and the data properly parsed. Further, expectations for performance, as well as performance metrics, require calibration. Lastly, high pace increases the cognitive burden on actors as the information load rises and as they struggle to gather and process the data load (Hayward, 2002). As Oliver, Calvard and Potočnik (2017) remind us, "Cognition-based and managerially induced limits share some common features. Both recognize limited capacity for attention and information processing. From the cognitive perspective, a crucial limiting factor of what an organization can do is determined by the ability of its members to make sense of what is happening around them; transgression of this limit is likely to lead to failure". Together, these factors suggest that increased pace will have a negative relationship on the experience-performance relationship in complex analytical learning contexts, thereby slowing the journey to the learning curve.

However, the time required to receive and process feedback about decision outcomes (the stimulus-feedback loop) should affect the experience performance relationship. In settings characterized by continuous production and learning by doing, performance feedback is instant. In such settings, increased pace directly hastens the journey to the learning curve. However, in contexts like strategic decision-making, the match between decision pace and the timing of performance feedback is especially critical in the early stages of learning. This is because strategic decisions are characterized by irreversibility or lock-in (decisions are not easily reversed and/or it is costly to do so). Early decisions (that is, those made when performance feedback is limited) are inherently risky since they may commit the firm to a course of action that may, if wrong, encumber the firm with significant opportunity costs. Such costs can materially increase the cost of learning.[5] Together, we posit that;

H2a: *The relationship between accumulated experience and the outcome of subsequent strategic decisions is negatively moderated by pace, such that organizations will learn more slowly when the pace of decision-making is high.*

H2b: *The relationship between accumulated experience and the outcome of subsequent strategic decisions is negatively moderated by pace, such that organizational performance will be lower when the pace of decision-making is high.*

Variance in Decision Outcomes

In H1, we contended that the relationship between accumulated experience and performance would be negative in its early stages and turn positive once sufficient experience has accumulated. An important concern is how the variance in decision outcomes, or performance, moderates that relationship. Variance in decision outcomes is, of course, required for learning (Madsen 2009). At issue, however, is the *extent* to which the level of variance shapes the learning experience.

Variance in early outcomes is critical to the learning process. Variance helps actors gain insight into causal relationships, and facilitates recognition of the patterns within the data and identification of the potential high and low boundaries of performance. Variance allows decision-makers to focus on finding patterns behind the variability, to parse data and focus on critical factors, and to engage in inductive and deductive reasoning. March and Simon (1958) note that the importance of variance is amplified when experience is limited;

[5] While those faced with strategic decisions may not have the luxury of postponing decisions until more information becomes available due to the actions of competitors, the strategy literature often recommends an option-based approach, in which the timing of decisions is linked to the availability of information (Tong & Reuer, 2007).

"Theories that emphasize the sequential consideration of a relatively small number of alternatives (Simon 1955; March and Simon 1958), that treat slack and search as stimulated or reduced by a comparison of performance with aspirations (Cyert and March 1963; Levinthal and March 1981; Singh 1986), or that highlight the significance of order of presentation and agenda effects (Cohen, March and Olsen 1972; Kingdon 1984) are all reminders that understanding action in the face of incomplete information may depend more on ideas about attention than on ideas about decision" (1958 p.1412).

While limited experience makes interpretation of variance difficult, the 'optimal' amount of variance is difficult to determine as its amplitude is both a product of, and is shaped by prior experience. That is to say, the importance of variance to learning changes as experience accumulates. For example, in the early stages of experience accumulation, variance is welcome since it provides rich information. The magnitude of variance is also important because it shapes motivation (large failures motivate greater attention and concern than low or near failures (Haunschild et al., 2015), and drives information content (Zhao & Olivera, 2006). Higher levels of variance in the early stages of experience accumulation should motivate learning and enhance performance.

But, how might that mechanism work? Existing research suggests it might affect the experience performance relationship in two main ways. First, it might affect the number of experiences required to reach the learning curve. High variance increases the information content of decisions, and provides better information about the performance frontiers of the activity as well as information about decision drivers. In contrast, invariance impairs our ability to learn. Oliver et al (2017) have argued that "the same measures that make a system safe and predictable may introduce restrictions on cognition". That is, low variance environments reduce the ability to recognize events outside of the normal and expected. Low to moderate levels of variance might thus be associated with slower rates of learning as the information content of experience is reduced.

Variance should also be related to performance through the experience-performance nexus. High variance might help the organizations reach the learning curve faster, thus increasing income and reducing the cost of reaching the learning curve. High variance might also allow for quicker refinement of decision making, more rapid error correction, and lead to a reduction in the cost of learning. That is, the rate of learning may change as variance rises. On the other hand, invariance and low variance reduces the information content of performance outcomes, extends the period required for learning, and slows the processes of discovery. Put simply, when outcomes are invariant, knowledge about the parameters of prospective performance is absent. Organizations might thus suffer lower levels of motivation than organizations whose outcomes are more variable. It follows that variance will affect both the amount of experience required to reach the learning curve, and its cost. Accordingly, we hypothesize that;

H3a: The relationship between accumulated experience and outcome of subsequent strategic decisions is moderated by variance such that the amount of experience required for high variance groups to reach the learning curve will be less than the amount of experience required by low variance groups to reach the learning curve.

H3b*: The relationship between accumulated experience and outcome of subsequent strategic decisions is moderated by variance such that high variance groups will out-perform low variance groups .*

SAMPLE AND METHODS

Sample Our data was obtained from a global remittances firm that was founded in 2001 and grew over a 14-year period to become one of the dominant players in the industry. During that period, this firm opened 9,769 money transfer franchises in 2,640 cities across 14 European nations. Their business model consists of granting franchises to immigrant entrepreneurs who are located within different ethnic enclaves across cities in Europe. Franchisees use the parent firm's software, financial network, and financial resources to transfer funds to individuals around the world. The firm profits from fees on transfers and from earned interest on the flow of funds. Franchisees receive a base commission plus an incentive based on the volume of remittances. The firm relies on its software to monitor franchisee performance, and reduces its risk of fraudulent transfers by imposing a daily limit on the total amount of funds a franchise can transfer. Firm practice is to give new franchisees a daily limit of 3000 euro. The daily limit is then increased or decreased to meet demand and franchisee performance.

To succeed, the firm must match a particular franchisee located within the host city to the chosen geographic target (city and country). In interviews, executives shared their belief that franchisees who are reputable and have the social skills, network ties, and standing within the targeted ethnic enclave are successful. Since success rests on the quality of the match between the franchisee and target host country and home nation combination, we identified 530 such unique home-and-host country pairs (example: Pakistani-owned franchisees in Spain), each of which we view as a unique remittance market that is best served by a uniquely qualified franchisee. After screening the data for missing values and small cell sizes (e.g., home-host country pairs that are served by fewer than three franchises), the sample was reduced to 165 market segments in which a total of 3,620 franchises (from 13 host nations and 64 home nations) were approved.

Measures

Dependent Variable. The performance of a given franchisee is measured as the *Daily Transaction Volume* that a franchisee had on the 3rd of February, 2015. To assure comparability across cases, we use the number of days that elapsed between February 3, 2015 and the date the franchise was awarded as a covariate (*Franchise Age*) in our regression model.

Independent Variables. Consistent with the existing literature (e.g., Argote & Miron-Spektor, 2011), we measure *Accumulated Experience* as the number of franchises awarded in each specific origin-and-host country group prior to the focal decision date. We measure *Pace* as a moving average of days between the prior three decisions and the focal decision. We compute *Performance Variance* using the *Daily Transaction Volume* for the three decisions prior to the focal decision.[6]

Covariates. Since the aim of this study is to understand how accumulated experience and attributes of that experience, shape performance, we employ covariates to account for exogenous sources of variance that are incidental to the question at hand. At the market level, we use *Market Size (Host)* and *Market Size (Home)* to control for heterogeneity in remittance market size, and we control for the absolute *Economic Distance* between the potential size of those markets by computing the absolute value of the difference in per capita GDP between host and home nations. Data on per capita GDP was acquired from the UN's macroeconomic databases. We also we account for the focal city's size by controlling for its *Population* and for the level of market development with the *Franchise Count.* At the local market level, we control for the *Franchise Age* and for the *Franchisee Age* and *Franchisee Gender.* Finally, since a limited number of franchisees own multiple franchises, we control the *Number of Franchises* operated by each franchisee.

Methods. Because some variables were highly skewed due to relative cell sizes and the diversity of markets included in this study, conventional distribution-correction procedures (e.g., log and

[6] Robustness tests indicate no material difference were observed when these variables were computed using 2 to 5 past decisions.

root) were employed where indicated. To address problematic collinearity between our DV and *Pace* and *Performance Variance,* we used orthogonalization procedures recommended by Sine, Mitsuhashi, and Kirsch (2006). We also followed established convention (Cohen et al., 2003; 2013) and used standardized variables to compute our interactions and non-standardized variables to model our main effects. After following these procedures, the VIF of our saturated model (Model 3) was 1.98. Finally, since our variables were determined at the different hierarchical levels, we used multi-level regression analysis (Hackman, 2003; Hox, Moerbeek, & van de Schoot, 2010) and modeled home (franchisees' origin) and host-country levels as the main levels in our data. We used maximum likelihood estimation methods with random effects due to the presence of different intercepts for different decision groups.

RESULTS

Descriptive and correlation statistics are reported in Table 1. Inspection of the correlation table reveals no anomalies. The average Daily transaction volume of a franchise is 5,829€ (≈1,750,000€ yearly) and the average number of decisions in the 165 decision groups is 19. The mean for Pace was 27 decisions and the mean for Variance is 101 euro. Results of our regressions are reported in Table 2. Model 1 includes all control variables, Model 2 reports the main effects for all independent variables and the quadratic effect for Accumulated Experience. Model 3 reports results for all hypotheses. Plots of all relationships are reported in Figures 1 through 3.

Consistent with H1, model 3 of Table 2 indicates that the relationship between Accumulated Experience and Daily Transaction Limit is indeed u-shaped: Both the main effect (0.09; $p \leq 0.001$) and square of Accumulated Experience (0.09; $p \leq 0.001$) are significant and in the hypothesized direction. [7] The turning point of the u-shaped curve is 18 decisions. We also observe the predicted relationships for both H2 (Pace) and H3 (Variance). Plots of the relationship are presented in Figures 1(a), 1(b), and Figure 2. Figure 1(a) shows the plot for full range of Accumulated Experience, and figure 1(b) (and all subsequent figures) are displayed using a range of 0-50 cases for Accumulated Experience. Doing so facilitates examination of the range of observations that are most relevant to our theory. The observed values for Pace (0.07; $p \leq 0.01$), and Accumulated Experience x Pace (0.09: $p \leq 0.001$), along with a non-significant relationship between the square of Accumulated Experience and Pace, indicate that Pace has a linear (additive) influence on the curvilinear relationship between Accumulated Experience and our DV. That is to say, a reduced Pace causes the position of the curve to shift upward and to the left. This is evident in the plot of H2 (Figure 2) which shows that a slower pace both hastens the journey to the learning curve (the turning point when pace is low is 11 decisions compared to 30 decisions) and reduces the cost of reaching the learning curve, as indicated by the relative positions of the two curves. We conclude H1 and H2a and H2b are supported.

The observed values for Variance (0.01; $p \leq 0.001$), Accumulated Experience x Variance (*n.s.*) and Accumulated Experience^2 x Variance (-0.02: $p \leq 0.001$) indicate that Variance has a linear by curvilinear (a multiplicative) influence on the relationship between Accumulated Experience and our DV. That is to say, consistent with our conjecture that variance increases (decreases) the information content of an event, Variance causes the shape of the focal curvilinear relationship to change: Specifically, it becomes steeper (flattens). However, increased variance does not materially change the turning point. This is evident in the plot of H3 (Figure 3) which shows that greater variance reduces the cost of learning (the revenue differential between

[7] To limit redundancy, we only report the observed values for our IV (*Accumulated Experience)* once and do not repeat them when reporting results for H2 and H3.

the two curves exceeds 500 euro per day) but does not hasten the journey to the learning curve (the turning point when Variance is high is 17 decisions compared to 21 decisions for the low condition). We conclude our data indicate support for H3b but not H3a.

ROBUSTNESS TESTS

Given the nature and limitations of our data, we conducted a variety of tests to probe the sensitivity of our data to specification and other forms of error. We began by following Anand et al. (2016) who observed in his study that accumulated experience may be endogenous to prior performance because firms are more likely to accumulate experience when successful. Accordingly, we tested for this possibility by adding Past Performance, Past Performance^2, and the product terms for the interaction of Past Performance and Past Performance^2 with our moderators into all models. Tests of Past Performance were repeated with the predictors for Variance included and excluded from our models. No material differences were observed across all these tests.

We also sought to address potential endogeneity issues by using an instrumental variable approach. To construct an instrumental variable, we followed Anand et al. (2016) and sought to create a measure that would reflect the level of the Accumulated Experience if the process of experience accumulation was random. If Accumulated Experience were indeed random, one might expect it to be proportional to the share of the corresponding immigrant-franchisee's diaspora in the total immigrant population in a host country. Tests confirmed this was indeed the case ($r = 0.64$ $p \le 0.001$). At the same time, the level of the randomly accumulated experience should not directly determine the Daily Transaction volume of an individual franchise (that is, it should be uncorrelated with the error term) – the second requirement for a valid instrumental variable. Since our model includes curvilinear relationships, we followed Haans et al. (2016) and created the separate instruments for Accumulated Experience (Random Accumulated Experience) and Accumulated Experience^2 (Random Accumulated Experience^2). To check if the use of the instrumental variables is justified, we then ran the Durbin-Wu-Haussman (DWH) augmented regression test (Davidson and MacKinnon, 1993) and failed to reject the null that the Accumulated Experience is exogenous. Results from the two-stage regression also suggested no substantial changes to our base model. Based on this analysis, we conclude it is unlikely that that the results are materially influenced by endogeneity.

We also conducted a series of robustness tests. First, we made sure that decision-makers were sensitive to *variance* in performance, and not the *direction* of past performance, by scoring the direction of the change in prior performance (1 if improved and 0 if declined) by summing the scores for the prior three outcomes, and then adding the variable, as well as its product with Accumulated Experience to Model 3. No material differences were observed. Second, we confirmed the presence of a quadratic relationship by following the procedures outlined by Lind and Mehlum (2010). For example, we split our sample at the mean and confirmed that the relationship between Daily Transaction Volume and Accumulated Experience is significant and negative below the mean and significant and positive above the mean. Third, we validated that the turning point was, in all cases, within the relevant range of our study. Fourth, we tested for spillover effects – that is, whether performance rose within the target market (e.g., Madrid) due to spillover effects from learning in other markets – by including in our models the number of franchises serving the same host-home market (e.g., Spain : Pakistan) from all markets except Madrid. Again, no material differences in our results were observed. Finally, we tested the robustness of our specifications for Pace and Variance by computing these variables for the 2 through 5 past decisions. In this case, we found that that the significance of Variance and Pace varied but did not fall to insignificance. We conclude our results are reasonably robust and that our models are correctly specified.

DISCUSSION

In this paper, we drew upon the organizational learning and strategic decision-making literatures to develop theory about learning from limited experience, and explore the nature of the relationship between accumulated experience and the outcomes of strategic decisions. A unique sample of decisions about franchise applicants from a global remittances firm allowed us to examine repeated strategic decisions across a variety of markets and over time, and made it possible to generate reasonably robust estimates of how long it took this organization to reach the learning curve. Results suggest that the overall relationship is u-shaped; it declines initially and, once sufficient experience accumulates, it rises in a manner that resembles the traditional learning curve.

We also identified two variables, the pace of decision making and variance in outcome performance that moderate the cost and speed of the journey to the learning curve. Specifically, our data indicate that a slower pace of decision-making shortens the journey to the learning curve while reducing its cost. We also found that increased variance – which is associated with increased information content from early decisions – reduced the cost of reaching the learning curve but did not materially hasten that journey. The fact that increased pace was associated with significantly lower revenues is both intriguing and consistent with the fact that once awarded, franchises cannot be costlessly reversed. The award of a franchise to a poor performer thus creates risk significant opportunity cost to the franchisor, in the form of forgone earnings. Our setting thus appears to be theoretically consistent and representative of the types of challenges and consequences that characterize strategic learning.

The results of this study are both intriguing and worrisome. They are intriguing because they illustrate that strategic learning is difficult and that it takes time for sufficient experience to accumulate. They are also intriguing because they identify two variables that influence the accumulated experience – performance relationship. Our study suggests that allowing a sufficient interval between decisions when experience is limited yields substantial benefits. Doing so allows for a better fit between the nature of the decision and the performance feedback cycle, allows time for information processing and reflection, and for the accumulation of added evidence. Moreover, extending the period between decisions is advice that practitioners can readily implement. Findings about variance, meanwhile, underscore the critical relationship between the information content provided by an experience, and rates of learning. They also illustrate that when experience is limited, or outcomes are invariant, learning is difficult.

Our findings are, however, somewhat worrisome for strategic decision-makers because they underscore that even in the case of relatively simple but strategically important decisions about franchise applicants, it can take a significant number of events for the organization to learn consistently. Our results stand in contrast with the host of studies in the strategy literature which argue that effective learning can occur in cases involving few decisions and/or from data derived from heterogeneous contexts. While doing so is necessary, since strategic decisions are in fact rare and heterogeneous by nature, it remains that our study cautions scholars to perhaps be more tempered when reaching conclusions about strategic learning processes. A more nuanced perspective on strategic learning is, our data suggests, merited.

These results are consistent with the theory we developed about the challenges of strategic learning and, in particular, about the likelihood of negative outcomes in the initial learning phases – a question that had received scant attention in both the organizational and strategic learning literatures. The results of this study should also remind decision-makers that it takes time, and repeated experience, for organizations to accumulate the information needed to get to the learning curve. The relationship between variance and performance also underscores the need for decision-makers to carefully consider and evaluate information requirements. In this light, Kale and Singh's (2007) recommendation that firms strive to codify information early in the strategic learning process seems wise. Codification facilitates the accumulation of the information needed to sort out and understand causality and calibrate performance expectations. Indeed, findings for H2 indicate that making decisions prior to the receipt of feedback information about outcome performance can have long-run detrimental consequences for the enterprise.

Finally, our results are somewhat worrisome for strategic decision-makers because they suggest that there may be a requisite, and perhaps irreducible, number of decisions that must bemade before improved outcomes are likely. Yet strategic decisions are usually compelled by environmental change or competition, which increases the magnitude of the threat that hasty strategic decisions can entail. Strategic decision-makers might then be compelled to act and, in doing so, must increasingly rely on some of the learning strategies, such as learning from analogy and metaphor (March et al, 1996) and vicarious learning (Denrell, 2003) that the strategic learning literature has previously stressed.

Our findings, however, temper that advice in several important ways. First, to date the strategic learning literature has, as Anand et al. (2016) note, tended to presume that that effective learning is possible even in cases where experience is limited: Ergo, when faced with failure, fault must lie with the learners (i.e., mistake or errors), or with the learning process itself (e.g., failure to effectively transfer learning from past experience). In contrast, our theory and data underscore that attributes of the learning experience itself may not only complicate learning, but may also prevent it from occurring *until sufficient experience (and data)* has accumulated. Additional research about the attributes of decisions that facilitate/impair learning is indicated. Moreover, we theorize and find evidence suggesting the negative outcomes are especially likely when experience is limited. Thus, we believe that efforts aimed at identifying and exploring attributes of the learning experience, and developing a robust baseline for performance expectations when experience is limited, may yield surprising benefits and insight into the phenomenon.

Second, much of the strategic learning literature has relied on binary outcome variables, such as success or failure. While the nature and irreversibility of some strategic decisions, such as an acquisition or entry decision, makes the use of such variables theoretically appropriate, it remains that the overarching goal is to make *better* decisions. As this study illustrates, a research focus on the quality of strategic decision outcomes facilitates finer grained insight about the learning process, and the costs and benefits of activities that may hasten the journey to the learning curve. We believe a renewed focus on the quality of learning outcomes is merited.

Lastly, while it is unrealistic to anticipate that the strategic decision contexts are homogeneous or, indeed, that organizations have the luxury of learning from six, eight, or even eighteen decisions, our data suggests that repeated experience with a decision – whether in the same organization or with multiple organizations – should yield learning benefits. While our setting precludes a test of this conjecture (since we have no information about our decision-makers prior experience), it seems reasonable to conclude our data underscores that the impact of accumulated experience on the decision-maker may indeed prove critical to improved performance.

Like all studies, there are a number of limitations that restrict our ability to generalize from the data. The most critical is that we measure performance only once, and do so on a date that is distal from date of the decisions that we study. While this constrains inference, it has the peculiar benefit of mitigating the idiosyncratic effects of local market conditions upon outcomes at the time of the decision, such as differences in levels of training provided to franchisees, varying levels of motivation and so forth. While we believe our measures are valid, it remains that we must infer (rather than directly measure) information about the time that it took decision-makers to learn how to reliably identify high potential candidates. While we wish we had better measures, the fact our results are theoretically consistent with our conjectures, and empirically reliable, provides some assurance about the merits of our study.

Other important limitations concern the extent to which our setting can be viewed as representative of the strategic learning context. While it is readily evident these decisions are indeed strategic in nature, they are not as complex and do not involve as many decision-makers as are often engaged in mergers and acquisitions and other strategic decisions that the strategic learning literature has previously explored. Further, these strategic decisions are, in the main, not made by members of the top management team but rather, are delegated to regional managers. While this feature makes these strategic decisions less classically strategic than many of the decisions studied in the strategic learning literature, it is also true that many of the more classic strategic decisions studied are also not made exclusively by top executives. Rather, they are delegated to experts in product development, marketing, finance, and other activities that the decision involves. One might also challenge the representativeness of the sample on the grounds that these decisions are less complex than most studied within this literature, such as mergers and acquisitions. Yet, it seems to us that the absence of complexity, along with the decision volume, allows us to study questions that hitherto could not be explored when studying other strategic decisions. Moreover, if learning takes time in this less complex environment, we should expect it to take even more time more complex cases.

Another limitation is that we have little information about who actually made the decision. For example, we do not have information about how many decision makers were involved in decisions at different moments of time, and we lack information about their duties or organizational tenure, as well as the specific criteria they used to select franchisees. Yet, like other fields that study organizational phenomenon at a higher level of analysis, along with the sheer size of the study, both in terms of number of observations and heterogeneity across markets, allow us to explore questions that are rarely studied. They also provide a unique perspective about learning curves and the strategic learning process. As a result, this study is distinctive and informative about issues that had previously escaped both theoretical and empirical scrutiny.

Past research about strategic learning has been productive, but absent the ability to investigate the phenomenon with large samples and relatively homogeneous decisions, we lacked insight into important questions about how long it takes to get to the learning curve, as well as about how different attributes shape that experience. The results of this study inform that question and perhaps serve to shift the level of analysis for research about strategic learning from the level of the decision-maker to the contextual factors that also shape that process.

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TABLES AND FIGURES

Table 1. Descriptive statistics: Means; Standard deviations; and Correlations

	Variable	Mean	s.d.	1	2	3	4	5	6
1	Daily Transaction volume[1]	8.22	0.77	1					
2	Market size (Host)	18.06	5.04	0.06***	1				
3	Market size (Home)[2]	0.69	0.45	-0.02	0.41***	1			
4	Economic distance[1]	1.45	0.80	0.03*	-0.11***	-0.23***	1		
5	Population	1.78	2.42	0.07***	0.35***	0.23***	0.13***	1	
6	Number of Franchises[1]	2.61	1.80	-0.05***	0.11***	-0.04**	0.13***	0.55***	1
7	Franchise's Type	0.34	0.48	0.16***	0.05**	0.01	0.13***	0.24***	0.09***
8	Franchise Age	5.90	0.69	0.16***	0.02	0.09***	0.03†	0.02	-0.14***
9	Franchisee Age[1]	39.7	9.50	0.08***	0.04**	0.04**	0.02	0.08***	-0.01
10	Franchisee Gender	0.76	0.43	0.02	-0.02	-0.04*	0.13***	0.02	0.01
11	Units per Franchisee[1]	0.12	0.33	0.04*	-0.05**	-0.10***	-0.05**	-0.02	0.08***
12	Accumulated experience[1]	3.81	1.30	-0.16***	0.20***	0.15***	0.05**	0.01	0.17***
13	Pace[1]	2.25	1.41	0.14***	-0.21***	-0.17***	-0.02	-0.04**	-0.14***
14	Performance Variance[1]	12.97	5.66	0.15***	-0.01	-0.05**	0.03†	0.01	-0.04*

	Variable	7	8	9	10	11	12	13	14
7	Franchise's Type	1							
8	Franchise Age	-0.01	1						
9	Franchisee Age	0.09***	0.08***	1					
10	Franchisee Gender	0.06***	-0.00	0.07***	1				
11	Units per Franchisee	0.10***	-0.00	-0.01	0.01	1			
12	Accumulated experience	-0.08***	-0.39***	-0.21***	0.11***	0.09***	1		
13	Pace	0.04***	0.23***	0.16***	-0.10***	-0.12***	-0.82***	1	
14	Performance Variance	0.06***	0.30***	0.04**	0.01	-0.02	-0.18***	0.16***	1

† $p \leq 0.10$, [1] Log transformed, [2] Root transformed
* $p \leq 0.05$,
** $p \leq 0.01$,
*** $p \leq 0.001$

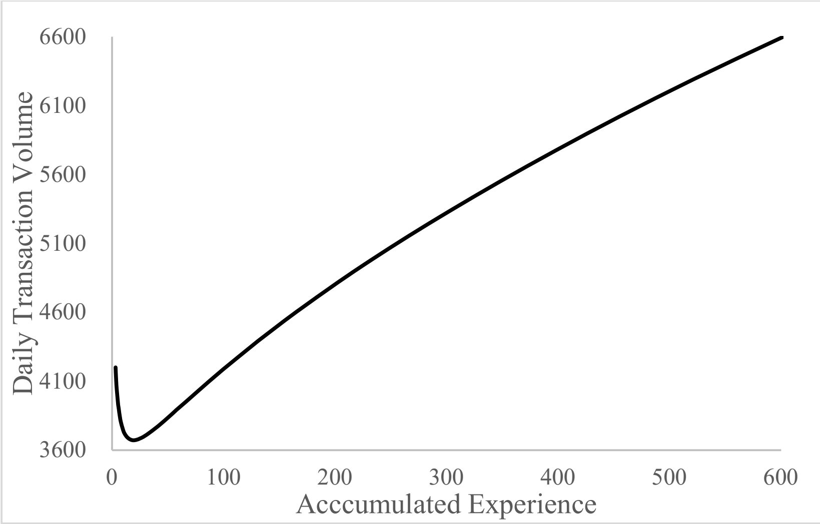
Table 2. Mixed-effects linear regression analysis

Daily Transaction Volume	**Model 1**		**Model 2**		**Model 3**	
	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.
Market Size (Host)	-0.01	(0.01)	-0.01	(0.01)	-0.01	(0.01)
Market Size (Home)	-0.02	(0.04)	-0.02	(0.04)	-0.02	(0.04)
Economic Distance	-0.00	(0.02)	-0.00	(0.01)	-0.00	(0.02)
Population	0.01 *	(0.01)	0.01 *	(0.01)	0.01 *	(0.01)
Number of Franchises	-0.02	(0.01)	-0.02	(0.01)	-0.02	(0.01)
Franchise's type	0.08	(0.08)	0.09	(0.08)	0.09	(0.08)
Franchise age	0.17 ***	(0.05)	0.19 ***	(0.05)	0.19 ***	(0.05)
Franchisee age	0.00	(0.00)	0.00	(0.00)	0.00	(0.00)
Franchisee's gender	0.01	(0.03)	0.01	(0.03)	0.00	(0.03)
Units per franchisee	0.19 **	(0.06)	0.19 **	(0.06)	0.20 **	(0.06)
Accumulated experience	0.07 *	(0.03)	0.08 *	(0.03)	0.09 **	(0.03)
Pace	0.07 ***	(0.01)	0.07 ***	(0.02)	0.07 **	(0.03)
Performance Variance	0.01 ***	(0.00)	0.01 ***	(0.00)	0.01 ***	(0.00)
Acc. Experience^2			0.03 *	(0.01)	0.09 ***	(0.02)
Acc. Experience x Pace					0.09 ***	(0.02)
Acc. Experience^2 x Pace					0.02	(0.01)
Acc. Experience x Variance					-0.01	(0.01)
Acc. Experience^2 x Variance					-0.02 ***	(0.01)
AIC	7,819		7,817		7,807	
BIC	7,900		7,898		7,893	
N – Markets	165		165		165	
N - Decisions	3,620		3,620		3,620	

† $p \leq 0.10$, * $p \leq 0.05$, ** $p \leq 0.01$, *** $p \leq 0.001$

Figure 1. Accumulated Experience (H1)

A. **Accumulated Experience (0-600 cases)**



B. **Accumulated Experience (0-50 cases)**

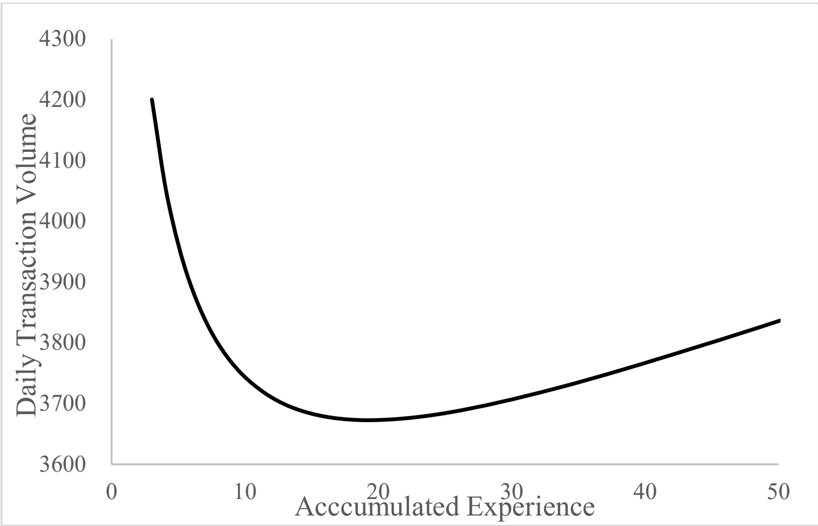


Figure 2. Pace (H2)

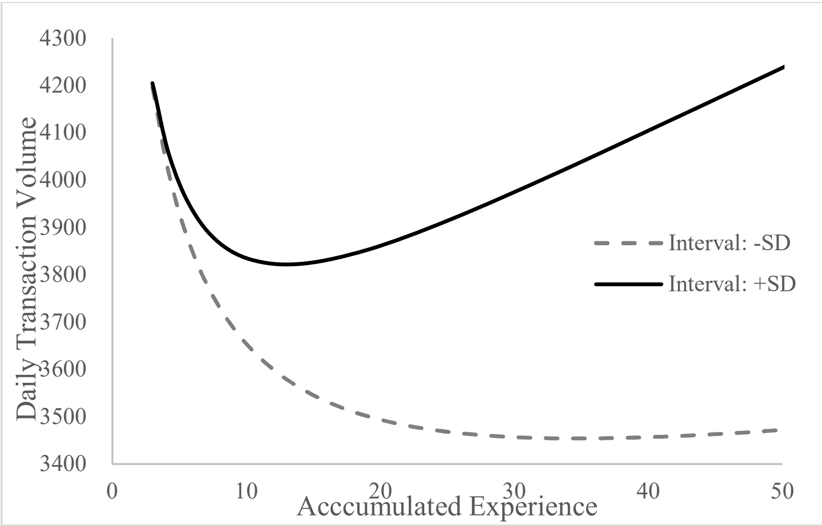


Figure 3. Variance (H3)