The Learning Effects of Monitoring

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ABSTRACT: This paper investigates the relationship between monitoring, decision-making, and learning among lower level employees. We exploit a field-research setting in which business units vary in the “tightness” with which they monitor employee decisions. We find that tighter monitoring gives rise to implicit incentives in the form of sharp increases in employee termination linked to “excessive” use of decision-rights. Consistent with these implicit incentives, we find that employees in tightly monitored business units are less likely than their loosely monitored counterparts to: (1) use decision-rights; and (2) adjust for local information, including historical performance data, in their decisions. These decision-making patterns are associated with large and systematic differences in learning rates across business units. Learning is concentrated in business units with “loose monitoring” and entirely absent in those with “tight monitoring”. The results are consistent with an experimentation hypothesis in which tight monitoring of decisions leads to more control but less learning.

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I. Introduction

It is well understood that management control choices in organizations need to balance the encouragement of effective decision-making with the mitigation of risky outcomes due to either poor decisions or employee opportunism (Baiman 1990; Merchant and Van der Stede 2003; Simons 2000). However, an additional consideration that is often overlooked in the academic literature is that management control choices that alter employee decision-making can also have a powerful influence on learning (Sprinkle 2000; Lee et al. 2004; Campbell 2008). In this paper, we add to the limited literature on this topic by investigating the relationship between monitoring and the decision-making patterns and learning rates of lower level employees.

Determining appropriate management controls for lower level employees is an important issue for most organizations. These employees often have unique knowledge about an organization’s individual customers, its local markets, and its production processes. The delegation of decision-rights to such employees can allow organizations to gain the benefits from effective and timely use of local information without incurring the costs of collecting and transmitting this information to top management (Jensen and Meckling 1992; Nagar 2002). This delegation, however, comes with the obvious management control problem of ensuring that employees use their decision-rights in the best interest of the organization.

One mechanism that is widely used across organizations to achieve management control in this context is direct monitoring of employee decision-making via management reports or other review processes. For example, bank officers may have discretion in underwriting consumer loans, but most banks have in place “exception reports” which flag loans underwritten outside of formal guidelines for further review. Similarly, a local sales representative may have wide latitude in granting price discounts to local clients, but headquarters may have guidelines in
place for flagging and reviewing “excessive” price discounting. In this paper, we focus on the
decision-making and learning implications of this form of “exception-report” monitoring.

These types of monitoring mechanisms are expected to have a direct influence on
employee decision-making. Employees facing more “evaluative pressure” are less prone to
opportunism and less likely to experiment or take risky decisions, preferring instead the certainty
of managing towards explicit guidelines (Nagin et al. 2002; Lee et al. 2004; Hunton 2008).

The learning implications of monitoring are less clear. As employees use their decision
rights, they may learn over time the conditions under which their decisions are effective. If
monitoring leads to less use of discretion by employees, then they are in effect performing fewer
“experiments” and have fewer opportunities to learn (Lee et al. 2004). This “experimentation
hypothesis” would predict negative learning implications of increased monitoring. Alternatively,
if the threat of detection inherent in monitoring leads employees to be more selective in utilizing
decision rights or to expend more effort in learning how to use them effectively, then monitoring
may lead to enhanced learning. This “selective utilization” hypothesis would predict positive
learning implications of increased monitoring. Which of these alternatives is likely to prevail is
an open empirical question which we address in this paper.

Our findings, based on field and quantitative data from the MGM-Mirage Group,
generally point to a tradeoff between employee learning and the intensity by which their
decisions are monitored by superiors. Consistent with the “experimentation hypothesis”,
employees in “tightly monitored” business units face strong implicit incentives to experiment
less by deviating less often from explicit decision guidelines and have fewer opportunities to
learn. These decision-making patterns are associated with large and systematic differences in
learning rates across business units with learning concentrated in those with “loose monitoring”
and entirely absent in those with “tight monitoring”.

This study contributes to managerial accounting research by documenting how monitoring can influence the implicit incentives faced by employees in ways that alter both their decision-making patterns and rates of learning. With the exception of a few studies, the relationship between management control choices and learning is a topic that has been largely unexplored in the accounting literature (Campbell 2008; Sprinkle 2000). Similarly, much of the literature on learning in organizations has documented variation in rates of learning both within and across organizations but, with the exception of a handful of studies, has been relatively silent about the sources of this variation (Pisano et al. 2001; Lapre and Tsikriktsis 2006; Wiersma 2007). Our results contribute to this literature by documenting systematic variation in rates of learning attributable to differences in management control practices across business units.

II. Literature Review

Our paper draws on, and extends, two broad and related research streams: (1) studies on learning by experience and the “learning curve” and (2) theoretical and empirical work on monitoring and its influence on behaviors related to experimentation, risky decision-making, and opportunism all of which we view as potentially important antecedents to learning.

Learning by Experience and Variation in the “Learning Curve”

The literature on organizational learning is large and diverse. Studies in this literature tend to distinguish learning on at least two dimensions: (1) the level at which learning takes place and (2) the source of knowledge acquisition. Learning has been documented at the individual, team, business unit, and organizational levels and has been attributed to a variety of different underlying sources of knowledge acquisition ranging from deliberate organizational search processes to learning by experience (Huber 1991; Dodgson 1993).

Our study focuses on differences in individual rates of learning across business units with different control structures and is most conceptually related to the literature on learning by
experience. Collectively, this literature has shown a fairly robust relationship between cumulative experience and performance improvement. This “learning curve” phenomenon has been documented in a variety of contexts and with respect to a variety of different measures of experience (e.g. production volume, time) and performance (e.g. cost reduction, customer satisfaction) (Argote and Epple 1990; Pisano et al. 2001; Lapre and Tsikriktsis 2006).

Beyond demonstrating the existence of learning, this literature has also documented significant variation in rates of learning both across and within organizations (Jarmin 1994; Pisano et al. 2001; Lapre and Tsikriktsis 2006; Wiersma 2007). Learning curves have been found to vary with labor versus capital intensity (Adler and Clark 1991); the degree of vertical integration (Sorenson 2003); the degree of task heterogeneity (Wiersma 2007); and the explicit (e.g. bonus) and implicit (e.g. promotion) incentives faced by individuals (Campbell 2008; Sprinkle 2000). This paper extends this line of inquiry to examine monitoring as a factor that can have an important influence on individual rates of learning within organizations.

**Monitoring and Antecedents to Learning**

Studies on actual rates of learning within organizations have been relatively silent on the role of monitoring and other management control choices. There has been more progress in this area within a diverse literature that recognizes experimentation – defined generally as a trial-and-error process where each trial generates new insights – as an important antecedent to learning (Sitkin 1992; Thomke 1998; Thomke et al. 1998). Researchers have shown that perceptions of evaluative pressure, arising from the degree to which an organization’s formal and informal reward systems are viewed as punishing failure, negatively influence experimentation (Edmondson 1999, Lee et al. 2004). Our study is conceptually related to these in that we focus on monitoring as a mechanism that can give rise to evaluative pressure. We also characterize the use of decision-rights as a form of experimentation in which employees can deviate from formal
decision-guidelines, observe outcomes, and learn about the quality of their decisions. However, unlike our study which focuses on monitoring as an explicit management control choice, these studies rely largely on individual perceptions of evaluative pressure. The actual underlying reward systems and management control structures that affect experimentation are typically not well specified.

The accounting literature focuses on the related issue of managerial willingness to undertake risky investment projects.¹ Similar to the notion of experimentation, risky investment decisions involve *ex ante* uncertainty about the outcomes of the decision and potential *ex post* opportunities to learn from “mistakes”. This literature speaks more directly to the impacts of monitoring which has been shown in experimental settings to reduce participant’s willingness to undertake risky investment projects (Hunton 2008). A related literature in economics has shown reductions in employee opportunism due to increased monitoring (Wiseman and Gomez-Mejia 1988; Nagin et al. 2002).

In general, these literatures document the potential influence of monitoring on experimentation, risky decision making, and employee effort – all of which can be important antecedents to learning – but do not make the link to actual learning within organizations. Our paper fills this gap by focusing on the existence and magnitude of the relationship between monitoring and actual individual rates of learning by experience.

**Empirical Predictions on the Relationship between Monitoring and Learning**

The predictions that emerge from these literatures about the relationship between monitoring and learning are not straightforward. The arguments from the literatures on experimentation and risky decision-making in organizations would predict that more intensive monitoring would lead employees to use decision-rights less frequently and, in effect, perform

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¹ See Baiman (1990) or Lambert (2001) for a review of some of this extensive literature.
fewer “experiments” leading to reduced opportunities for learning. This “experimentation hypothesis” would predict negative learning implications of increased monitoring.

On the other hand, theoretical models of information acquisition within organizations have distinguished between employee effort aimed at collecting decision-relevant information and effort aimed at using such information effectively on the organization’s behalf (Lambert 1986; Demski and Sappington 1987). If the threat of detection inherent in monitoring leads employees not only to supply more productive effort as in Nagin et al. (2002) but also to expend more effort in pre-decision information collection activities, then monitoring may lead to enhanced learning via experience in this task. Employees could use decision-rights less frequently but do so more selectively based on better pre-decision information. This “selective utilization” hypothesis would predict positive learning implications of increased monitoring.

III. Research Setting

The data for this study come from six of the major hotel properties of MGM-Mirage Holdings that share a common information system for collecting customer performance data. As of the time of this study, the group operates numerous properties within Las Vegas and across the United States and Asia. Although these properties have been united under the same corporate group through a series of acquisitions, each property retains its own personality and is managed independently of other MGM-Mirage holdings. The typical property in the group includes a casino, which offers activities such as table games, slot machines, and video poker; a hotel, which ranges in size to over 5,000 rooms; and entertainment offerings including live shows, restaurants, and bars and nightclubs.

Customer Profitability

Properties in the MGM-Mirage group place great emphasis on managing the profitability of their gaming (e.g. casino) customers. Each property tracks customer gaming behavior and
performance in detail through the "Players Club" loyalty card and associated database. The Players Club database also tracks all “comps”, which may include reduced hotel and entertainment costs, free restaurant meals, or tickets for a show. Customers receive comps based on both the money they wager—a figure that determines their current profitability—and expected future gaming behavior. MGM executives commonly refer to customers by their expected gambling expenditures per trip. For example, a luxury suite might be offered to a “$30,000 per-trip customer.” The basic components of gaming customer profitability are the gaming standard margin and the comps.

The basis of gaming customer profitability is the casino’s so-called “theoretical win” from the customer—the margin that the property could theoretically make from the amount the customer bet based on the mix of games played and their respective house advantage—not the “actual win.” One employee explained that the group did not want to penalize lucky customers: “…we don't care if you win or lose as long as you give us a shot at your money.”

The amounts bet are recorded differently at slot machines and table games. Slot machine play is recorded in great detail by the Players Club card, which the customer inserts in the machine. In contrast, in table games—e.g. blackjack, roulette, baccarat or craps—floormen “rate the play” of the customers on handwritten slips, which reflect the floorman’s assessment of the average bet, time played, and speed of play. Properties are able to trace around 65% of all slot revenues and 85% of all table revenues to individual Players Club customers.

Data captured in the database via the Players Club card covers more than ten years of operations and more than 8 million customers. In the calculation of customer profitability, costs such as operations and marketing personnel, equipment maintenance, and real estate are not assigned to the customer.

Comps
Comps are considered a customer-specific expense because they are used to reward gaming behavior. Gaming customer profitability is calculated by subtracting the comps from the theoretical win. If the comps are soft costs in the form of complimentary services provided by the property, they are recorded at the value at which they are purchased by full-paying customers. Any other complimentary service that implies a payment to an outside provider (for instance, reimbursements for plane tickets) is recorded at its full amount.

**Casino Hosts**

Individual properties rely heavily on employees known as “casino hosts” in order to initiate, manage, and ensure the profitability of customer relationships. Hosts interact with all segments of customers whose gambling levels justify comps. Prior to a trip, many customers call their host to arrange for room and show reservations. One host explained that she is the “go-to person in Vegas” for her clients, getting them priority tickets and access to “the most coveted clubs.” She keeps track of her clients’ travel information, greeting them personally when they arrive or arranging for a colleague to meet them if she is away from the property. Moreover, if a client has not visited the property in a while, she calls them “to understand why and bring them back.” Hosts use a combination of subjective observation and historical customer data to inform their decisions. New clients flagged by the system by their level of play while at the property or captured by the MGM-Mirage network of branches are randomly assigned to a host. Hosts may also add referrals from existing customers to their portfolio.

**Decision-Rights, Monitoring, and Incentives for Casino Hosts**

Casino hosts ultimately have decision rights on the comps awarded to their customers. They are free to choose the comps under the general guideline that the dollar value awarded as a percentage of the customer's theoretical win on the current trip—known as “comp percentage”—does not exceed 40%. This explicit definition of decision-rights for casino hosts appears to be common practice in the industry. According to one highly experienced senior executive we
interviewed, “…the general rule of thumb in the industry is 40% for the maximum comp percentage. This has been true for at least the past 20 years.” However, if the host believes that a customer is likely to be highly profitable in the future they can, and often do, use their decision-rights to award comps in excess of the 40% limit. In those cases, an “exception report” is triggered for review by the CFO of the property. As discussed in the next section, an important feature of this site for our research purposes is that properties vary substantially in the intensity with which host decisions are monitored through this exception reporting process.

Two features of this site point to the relative exogeneity of these differences in control practices for purposes of this study. First, we examine decision-making and performance at the employee rather than property level. Casino hosts operate within a given control system that is exogenous from their perspective. Second, each of the properties were independently founded and brought under the same corporate umbrella through a process of mergers and acquisitions. Our interviews with both corporate and property level management suggested that these independent histories coupled with path-dependence in management practices, rather than corporate optimization, has led to these cross-property differences in control practices.

The level and type of comps awarded to a customer on a given trip are typically agreed upon between the host and the customer at the start of the trip based on the expected gaming behavior. If ex post customer play does not meet the expected level, the host can adjust the comp award downward to meet the 40% threshold. For example, as one host noted: “Customers can sweet-talk you into getting a suite, but if their play doesn’t justify it in the end, you can make adjustments to the expenses we will and will not cover.”

Interestingly, all incentives for hosts to directly manage the key decision variable of comp percentage appear to be implicit rather than explicit. Although there is no formulaic relationship between the hosts’ bonuses and performance indicators, the incentive plan for casino
hosts at MGM-Mirage's properties explicitly indicates that the hosts’ annual bonus will be determined by the following criteria: 60% is based on total gaming revenues for the property, consistent with an objective to reward team work; 15% on individual goals for acquiring new, and reactivating “inactive” customers; and 25% on subjective evaluation of the performance of the host by the property’s senior management. Incentives to limit comp awards appear to be primarily determined by the exception report review process but may also depend on managers’ view of comp levels in the subjective evaluation component of the bonus plan.

**The Casino Host Decision-Process**

As part of this study, we interviewed several casino hosts across properties and “shadowed” some of them as they performed their work. Our observations revealed that hosts consider their interactions with customers in the context of a relationship. They process both hard and soft information to support each comp decision, although the heuristics applied to hard information and the confidence with which they incorporate soft information differ from host to host. Additionally, they explicitly engage in conversations about comps in order to manage clients’ expectations.

In general, hosts take a *dynamic rather than static view of the financial performance of customer relationships*. One host explained: “I usually give it a couple of trips to see what happens. I want to see how that customer is likely to perform over the next year or so. When I overcomp a customer, I am looking at what that will mean for [his or her] profitability for the entire year.” Many hosts also spoke of customer loyalty, with one noting that he can usually evaluate loyalty “within three to six trips.” In short, it is clear that hosts’ expectations of future customer performance shape their individual comp decisions and that they think of customers in terms of “relationships.” One host described using comp discretion “based on longevity and
what I know about the customer”; another noted that it can be difficult to separate “the social relationship vs. the business relationship.”

Our interviews and observations suggest that hosts vary greatly in the relative extent to which they base their discretionary comp decisions on “hard” information contained in the firm’s database, such as average theoretical win in the last “N” trips, versus “soft” information based on local knowledge of customers. When asked about how they make comp decisions, hosts replied including expressions such as “nothing is black and white in what we do, it is all grey,” or “sometimes I have to take a shot at a customer.” Often, this soft information is in the form of behavioral cues which hosts believe can indicate a potentially valuable customer. For instance, one host looks at body language: “It probably makes sense to focus on the person sitting at the slot machine with his feet up and 500 credits in the machine.” While all hosts seem to rely on soft information to some extent, the more experienced hosts that we interviewed appeared more confident in their ability to incorporate such information into their decisions. According to one of these, “good customers play differently. I’ve been here a long time, and I just know when it makes sense to overcomp.”

We also observed considerable heterogeneity in the heuristics hosts have developed for incorporating hard information from the database into their comp decisions, as illustrated by the following comments: “I tend to do more of a trip-by-trip evaluation”; “I look at the past four trips, throw out the lowest one, and take the average of the remaining three. I’ll then update based on current play”; and “I look at both year-to-date theoretical win and lifetime to date.”

Customers are often very conscious of the comps they receive for their play. As one host noted, “people read books [on Vegas] and ask what they need to do to get this or that.” Consistent with their dynamic view of customer interaction, casino hosts tend to think carefully about the future implications of current discretionary comp decisions: “Once you have given too
much to a customer, you are stuck. When you get them back to their natural level they think you have taken away from them”.

Data

The source for this study, the Players Club database, contains data on over 9 million customer trips between 1993-2004. To focus on host level decision-making and learning, we restrict our sample to the 349,887 customer-trip observations with an assigned casino host. We exclude from our study customers who choose not to interact with hosts and those whose level of play does not warrant host interaction.

In several cases in the data, one-time customers with zero or very low levels of theoretical win (e.g. due to limited gaming, small bets, etc.) received comps valued in the tens of thousands of dollars. We eliminate these observations—which are likely attributable to family or friends of highly valuable customers—to arrive at our final sample.2

For each trip-level observation we observe the unique identity of the host interacting with the customer, the theoretical win for the customer on the trip, and the dollar value of comps awarded to the customer for that trip. Because we observe data from 1993 (the first year of the firm’s Players Club program and database) onwards, we can reconstruct each host’s history of interactions with individual customers.

IV. Empirical Tests and Results

Definition of Tight vs. Loose Monitoring and the Link to Implicit Incentives

Hosts have the discretion to award comps in excess of the 40% limit to manage the lifetime value of a customer. However, the “exception report” triggered by each such event creates an implicit incentive to limit the use of this decision right. The exception report sent to the property CFO provides information on the type and dollar value of comps awarded and the customer’s current and historical theoretical win.

2 We eliminate data from trips in which a player was awarded comps that were greater than 20 times the current trip theoretical win and in which a player was awarded comps when theoretical win was zero. This eliminates 0.38% of our trip-level observations.
Because the report is used differently across properties, there are also significant differences in the implicit incentives to limit the use of discretion. We characterize some properties as having “loose monitoring”. In these properties, the exception report is used in a relatively lax way. One representative property CFO said the report was used mainly to detect egregious cases of comps misuse, and another reported that review of the report was delegated to the director of player development. In these properties, management actions with respect to hosts usually took a broad perspective: “if we observe hosts systematically exceeding the 40% limit, we call them in to discuss their performance and develop an action plan when necessary.” By contrast, properties that we characterize as having “tight monitoring” use exception reports to monitor employee decision-making more intensively. A CFO of one such property explained: “I review the report every day and email the hosts, who have a week to respond. If I see something strange I call the host right away.” Another noted: “I ask hosts for a written explanation of all comps that are $200 or 5% above the limit. I read every single explanation and I further question about 10% of them.”

We base our definition of tight versus loose monitoring in part on qualitative interview based data as noted above but also in part on the observed frequency of monitoring inherent in each property’s exception reporting process. Table 1 provides descriptive information on both types of properties. In tight monitoring properties, host comp decisions are monitored daily by the CFO of the property and a broader review of each host’s overall customer portfolio is conducted at the end of each month. In loose monitoring properties, host comp decisions are monitored only once per week and the broader review of a host’s portfolio is conducted once per quarter. We shared this classification with several MGM-Mirage Group managers all of whom found it valid based on their own observations and experience.

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3 Frequency of monitoring is noted in accounting texts as a general feature of “tight” control systems (Merchant and Van der Stede 2003). Frequency of feedback can also influence perceptions of a loss of personal control by individuals (Ilgen et. al. 1979).
We further validated our classification of tight versus loose monitoring properties by examining the sensitivity of host exit from a property \((EXIT)\) to a variety of measures of host performance. If a property discourages overcomping, hosts not conforming with the comps guidelines will likely be asked to leave or will voluntarily leave when they realize their behavior is not condoned. To the extent that “excessive” use of decision-rights is linked to departure, hosts will face incentives to limit their use of decision-rights.

To examine the potential strength of these implicit incentives, and how they vary for properties with tight or loose monitoring, we estimate the following exit-performance relationship:

\[
P(\text{Exit}_{jt}) = f(\beta_0 + \beta_1 \text{CustomerGrowth}_{jt-1} + \beta_2 \text{TripsPerCustomerGrowth}_{jt-1} + \beta_3 \text{TheoreticalWinPerTripGrowth}_{jt-1} + \frac{\beta_4 \text{Discretion}}{100} \text{Overcomped}_{jt-1} + \frac{\beta_5 \text{ExcessComps}}{\text{TightMonitoring}_{jt-1}} + \beta_6 \text{Experience}_{jt-1} + \sum_{j=2}^{p} \gamma \text{Property}_{jt-1} + \sum_{t=1994}^{2003} \gamma \text{Year}_{jt} + e_{jt})
\]

(1)

Our dependent variable, \(\text{Exit}_{jt}\), is set equal to 1 if host \(j\) departs from property \(p\) during year \(t\). We model the probability of departure as a function of a number of host-level performance metrics including growth in the number of customers in the host’s portfolio \((\text{CustomerGrowth})\), growth in the number of trips per customer in the host’s portfolio \((\text{TripsPerCustomerGrowth})\), and growth in theoretical win per trip for these customers \((\text{TheoreticalWinPerTripGrowth})\). Because these metrics are primary objectives of MGM-Mirage’s properties, we expect each of them to be negatively associated with the probability of departure. All measures are aggregated at the host-year level.

We also include in the specification a number of measures of the extent to which hosts use decision-rights: the annual proportion of individual customer-trips managed by the host in which comps exceeded 40% of the theoretical win \((\text{Discretion%})\); an indicator for whether the portfolio comp percentage—i.e. the total annual comps awarded by a host divided by the total
theoretical win across all customers in the host’s portfolio—exceeded 40% (Overcomped); and a measure of the extent to which a host overcomped customers for the year, taking the value of the portfolio comp percentage minus 40% for hosts who overcomped and zero otherwise (ExcessComps). This last measure is of particular interest as it captures not only the extent to which a host awarded comps to individual customers outside of the 40% guideline but also the host’s failure to absorb any overcomping to individual customers in the portfolio overall. Thus, this measure partially captures the effectiveness of a host’s use of her decision-rights. As a result, we expect that, all else being equal, high levels of this measure would be associated with a higher probability of departure.

We interact ExcessComps with TightMonitoring, an indicator for whether the host is employed at any of the three properties which we classify as “tight monitoring.” If our classification of properties is valid, then we expect that an increase in ExcessComps will lead to a higher increase in the probability of departure for properties classified as having “tight monitoring” vs. those classified as having “loose monitoring.” As additional control variables, we include property indicators, year indicators, and Experience measured as the number of years a host has been employed at a property at the beginning of each year.

Table 2 contains results from logit estimation of equation (1). All standard errors are adjusted for clustering of observations within hosts over time prior to inference. Column 1 demonstrates that hosts who are able to grow their customer base or to improve the theoretical win generated per customer trip face a lower probability of departure. Managers with higher levels of experience face lower departure probabilities. Holding other performance metrics constant, hosts who are overcomped across all customers in their portfolios (Overcomped) are more likely to leave the organization. This increase in the probability of departure is increased further by the degree to which the host is overcomped (ExcessComps). Interestingly,
Discretion% is unrelated to the probability of departure. Overall, these results provide evidence of incentives in this organization whereby the use of decision rights (Discretion%) is not discouraged per se, but where hosts face strong implicit incentives for managing the effectiveness with which these decision rights are used.

The results in column 2 are largely consistent with those in column 1 but also point to the validity of our classification of properties in terms of tight versus loose monitoring. The coefficient on ExcessComps × TightMonitoring is positive and significant, suggesting that “overcomping” is more strongly discouraged in the properties that we classify as having tight monitoring compared to those we classify as having loose monitoring. These estimates show that a host with the mean levels of all performance measures and operating below the threshold comp percentage of 40% has a 0.3% probability of departing from the organization. An overcomped host in a “loose monitoring” property with the mean levels of all performance measures but operating with a portfolio level comp percentage in the 90th percentile has a probability of departure that is approximately four times higher at 1.3%. By contrast, a similar overcomped host in a “tight monitoring” property has a probability of exiting the organization of 6.3%, an increase of almost fivefold compared to the host in a “loose monitoring” property.4

In summary, the results in this section provide further support for the validity of our “tight” versus “loose” monitoring classification which appears to capture real differences in the implicit incentives faced by hosts when using their decision-rights. In the next two subsections, we explore whether host decision-making is consistent with these differences in implicit incentives and the implications, if any, for learning in this environment.

Does Decision-Making Vary across Properties with Tight versus Loose Monitoring?

4 We also estimated a version of eq. (1) which allowed separate coefficients on ExcessComps for each property. Coefficients for each tight monitoring property are larger than those for each loose monitoring property. The implied marginal effects for hosts with excess comps in the 90th percentile relative to those within the comp guideline of 40% holding all other variables at their mean are 0.30%, 1.04%, and 1.58% for loose monitoring and 3.65%, 6.51%, and 8.08% for tight monitoring properties respectively. All effects other than the 0.30% estimate are significant at least at the 10% level.
There are at least two potential effects of tighter monitoring on the exercise of decision-
rights: (1) employees may be less likely to use discretion to deviate from guidelines in general;
(2) employees may be more or less likely to incorporate local information, including historical
customer data, when making decisions about individual customers. The first effect is
straightforward: employees who are more likely to be penalized for mistakes are less likely to
“experiment” (Lee et al. 2004), preferring instead to manage towards explicit guidelines.

The second effect is not as straightforward. In many settings, including ours, operational
employees have access to local information that can signal when decision-rights should be
exercised to exceed guidelines. Such local information can be “hard” (e.g. historical information
on customers in the firm's database) or "soft" (e.g. from direct interaction with a customer). The
latter is not, while the former is, observable to non-local decision-makers. We might expect that
employees in tight-monitoring environments, where they face more pressure to make the “right”
decision, would be less likely to incorporate local information into their discretionary decisions.
This is particularly true for “soft” local information. In this case, if employees’ discretionary
decisions do not pay off in current or future customer performance (e.g. increased sales or
retention), then these decisions will be more difficult to justify to superiors in the organization.
However, to the extent that “hard” local information can be used as a basis for exercising
discretion, employees may be more likely to incorporate it in their decision making even in tight
monitoring environments. In particular, if employees facing outcome-based incentives (e.g.
customer growth or retention) feel restrained from making decisions based on “soft” information,
then they may be more willing to exercise decision-rights when justified by observable (to local
and non-local decision-makers) “hard” information.

Turning first to the question of whether employees in tight monitoring environments are
less likely to exercise decision-rights in general, the results presented in Table 3 demonstrate that
this is indeed the case. As measured by Discretion\%, hosts in tight-monitoring properties are less likely to exceed the 40% comp guidelines than those in loose-monitoring properties (mean for tight-monitoring properties=19.6%; mean for loose monitoring properties=29.2%; difference significant at p<.01). Hosts in tight-monitoring properties are also almost three times less likely than those in loose monitoring properties to be overcomped at a portfolio level (Overcomped) in any given year (mean for tight-monitoring properties=0.139; mean for loose monitoring properties=0.368; difference significant at p<.01). Finally, hosts in tight-monitoring properties award substantially less comps relative to the theoretical win of their customer portfolios (Comp\%) in a given year (mean for tight-monitoring properties=35.6%; mean for loose monitoring properties=59.8%; difference significant at p<.01). Overall, the results in Table 3 are consistent with implicit incentives arising from tight versus loose monitoring across properties. By all measures of the extent to which hosts are using decision rights, discretionary decisions which deviate from comp guidelines are significantly less prevalent in properties we classify as having tight monitoring.

Turning next to the question of whether employees in tight monitoring environments are more or less likely to use decision-rights based on local information, we develop and test an empirical model of host decisions at the individual customer-trip level. As is clear from the qualitative evidence presented in Section III, hosts vary significantly in both how, and the horizons over which, they combine "hard" (e.g. historical information on customers in the firm's database) and "soft" (e.g. direct observation of customer behavior) information in their decisions. Capturing the complexities of these decisions in observable data is not trivial. As an approximation, we characterize the casino host decision process as:

\[
COMP_{ipt} = \beta_1 TheoreticalWin_{ipt} + \beta_2 E_{ij} \left( \sum_{k=1}^{T} TheoreticalWin_{ipt+k} \right)
\]
where \( \text{COMP}_{ijpt} \) is the dollar value of comps awarded to customer 'i' by host 'j' at property 'p' during trip 't'. In this characterization of their decision process, hosts determine the dollar value of comps to award a customer based on two pieces of information: the observed theoretical win of the customer on the current trip \( (\text{TheoreticalWin}_{ijpt}) \) and the host's expectation of the customer's future theoretical win at the property \( (E_j(\sum_{k=1}^{T} \text{TheoreticalWin}_{ijpt+k})) \). The customer's future theoretical win at the property is determined by both the level of theoretical win per trip and the number of future trips to the property by the customer \( (T_i) \). If hosts simply award comps to customers based on their observed level of play during the current trip without using their decision-rights to exceed the 40% limit, then \( \beta_2 = 0 \) and \( \beta_1 \leq 0.40 \). Alternatively, if hosts use discretion to deviate from the prescribed 40% limit based on their expectations about the customer's level of future theoretical win at the property, then \( \beta_2 > 0 \) and \( \beta_1 \leq 0.40 \).

Consistent with our interviews and observations, we assume that hosts form expectations about future customer performance at the property based in part on historical data on the customer's theoretical win \( (\sum_{s=1}^{L_i} \text{TheoreticalWin}_{ijpt-s}) \) and in part based on idiosyncratic soft information about the customer observed by the host at the property during the customer's current trip \( (\alpha_{ijpt}) \).

The past number of trips, \( L_i \), considered for each customer depends on the horizon considered relevant by the host. The host may consider the full tenure of the customer relationship with the property in which case \( L_i \) would equal the total number of past trips by the customer to the property. Alternatively, hosts may discount information on older trips, in which case \( L_i \) would

---

5 The absence of the 'j' subscript in is intentional and captures the notion that hosts have incentives to bring customers back to the property even if that customer switches hosts in the future.

6 The absence of the 'j' subscript in is intentional and captures the notion that hosts are simply using the customer's past level of performance at the property to make inferences about performance in the future. The past performance of the customer need not be the result of trips in which the customer interacted with the host making the decision on the current trip.
be determined by a shorter time period. The soft information represented by $\alpha_{ijpt}$ can be of several types including direct interactions between the host and customer in which the host inquires about the intent of the customer on current and future trips, inferences the host makes about the customer's appearance and behavior, or any other local information the host gains outside of the systematic customer data captured in the firm's information system. With this characterization, the host comp decision can be modeled as:

$$COMP_{ijt} = \beta_1 \text{Theoretical Win}_{ijt} + \beta_2 \left( \sum_{s=1}^{L_i} \text{Theoretical Win}_{ijt-s} + \alpha_{ijt} \right)$$  

(2)

This characterization of the host decision process has intuitive appeal. Conditional on the customer’s current level of play, hosts increase (decrease) the comp awarded when the customer's past level of play is high (low) which may signal that the current trip is a deviation from a pattern of performance established by the customer in past trips. Similarly, hosts increase the comp percentage when they observe local information on the customer that suggests higher future levels of play at the property ($\alpha_{ijpt}$).

As evidenced by our interviews, the horizons considered relevant for decision making vary considerably across hosts. In our empirical specifications, we choose the relevant past horizon as the 18 months prior to the current trip start date. That is, in equation (2), we set $L_i$ equal to the number of past trips the customer has taken to the property within the 18-month period prior to the current trip. We make this choice for two primary reasons. First, a customer formally becomes classified as "inactive" if they have not returned for 18 months from their last trip to the property. Whether the customer remains active, and how active they remain, over the 18 months subsequent to the current trip appear to be salient criteria for decision-making in our setting. Second, while many hosts suggested that they consider the entire history of customer data in their decision-making, they almost universally noted that they discount information that is
greater than 18 to 24 months old. In the remainder of the paper, for each customer-host-property-trip observation, we refer to $\sum_{j=1}^{L} TheoreticalWin_{ijp-s}$ as $LagTheoreticalWin$. For empirical purposes, we estimate the following version of equation (2):

$$COMP_{ijp} = \hat{\beta}_1 TheoreticalWin_{ijp} + \hat{\beta}_2 LagTheoreticalWin_{ijp} + \sum_{j=2}^{6} \gamma_j Property_j + \sum_{k=1994}^{2003} \lambda_k Year_k + \mu_j + e_{ijp}$$

(2)

where $\mu_j$ denotes a host fixed effect controlled for through the use of a series of host indicators, and $Property$ and $Year$ represent property and year fixed effects respectively. To examine whether employees in tight monitoring environments are more or less likely to exercise decision-rights based on local customer information, we also estimate a version of equation (2’) where we allow the empirical weights, $\hat{\beta}_1$ and $\hat{\beta}_2$, on current and historical theoretical win to vary for tight versus loose monitoring properties.

Results from OLS estimation of equation (2’) are presented in Table 4. All standard errors are adjusted for clustering of observations within customers over time prior to inference. The results in column 1 demonstrate that, on average, hosts weight both current and past customer information in their comp decisions. The coefficient estimates show that, conditional on past customer performance, hosts on average award $0.218 in comps per dollar of current trip theoretical win – well within the comp guidelines of all properties. On average, the comp award is adjusted upward by $0.011 per dollar of historical theoretical win (over the previous 18 months). Based on the coefficient estimate on $LagTheoreticalWin$, a customer’s past performance would have to be significantly higher than that on the current trip for a host to substantively shift the average comp percentage to be in excess of the 40% guideline. For the

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7 Property fixed effects are largely subsumed by host fixed effects. However, there are 18 hosts who switch properties over our sample period. In practice, after controlling for host fixed effects, the property fixed effects are estimated based on data from this small sample of “switchers”. Not surprisingly given the small number of switchers, our results are not sensitive to either the omission of property fixed effects or to the omission of this small sample of switchers from the analysis.
median customer-trip in our sample, \( LagTheoreticalWin \) is approximately two times the current trip theoretical win while it is approximately 16 times current trip theoretical win for customer-trips in the 90\(^{th}\) percentile. For the median customer-trip, hosts would on average increase the comp percentage by 2.2\% (2*1.1\%) to 24\% whereas for the customer-trip in the 90\(^{th}\) percentile, the comp percentage would on average increase by 17.6\% (16*1.1\%) to 39.4\%. Thus, on average, past customer performance would have to deviate significantly from current trip performance for hosts to use decision-rights so as to exceed formal comp guidelines.

Column 2 contains the results from estimating a version of equation (2’) which allows the empirical weights on current and historical customer information to vary for properties with tight versus loose monitoring. The coefficient on \( TheoreticalWin_{t-k} \times TightMonitoring \) is negative and significant (coefficient=-0.061; p<0.01). This result is consistent with those in Table 3 and documents that hosts in properties with tight monitoring tend to have lower comp percentages compared with their loosely monitored counterparts. The coefficient estimates show that, conditional on past customer performance, hosts in properties with loose monitoring on average award $0.259 in comps per dollar of current trip theoretical win while those in properties with tight monitoring on average award $0.198 (0.259-0.061) per dollar of current trip theoretical win. The coefficient on \( LagTheoreticalWin_{t-k} \times TightMonitoring \) is negative and significant (coefficient=-0.007; p<0.01). On average, the comp award is adjusted upward by $0.015 per dollar of historical theoretical win (over the previous 18 months) for loose monitoring properties compared with $0.008 (0.015-.007) for tight monitoring properties. For the median customer-trip in our sample, hosts in loose monitoring properties would on average increase the comp percentage by 3\% (2*1.5\%) to 29\% whereas for the customer-trip in the 90\(^{th}\) percentile, the comp percentage for hosts in these properties would on average increase by 24\% (16*1.5\%) to approximately 50\% – well over the formal 40\% guideline. The comparable numbers for hosts in
tight monitoring properties are a 1.6% (2*0.8%) increase in the comp percentage for the median customer-trip and a 12.8% (16*0.8%) increase for a customer-trip in the 90th percentile of historical theoretical win – neither of these increases would lead hosts to exceed formal comp guidelines on average. Thus, hosts in tight monitoring properties tend to adjust comp awards less in response to historical customer information than their counterparts in loose monitoring properties.

Column 3 contains results from estimating a version of equation (2’) which allows the host trip-level comp decision for an individual customer to vary with the performance of the host’s entire customer portfolio. Specifically, we add the host-year level variables Overcomped, ExcessComps, and their interactions with TightMonitoring to the specification. Overcomped and ExcessComps are measured for the year prior to the year of the current customer trip. The qualitative data from our interviews with hosts (discussed in Section III) along with the empirical results linking host-performance to departure in Table 2 demonstrate that hosts face incentives to manage their entire customer portfolios in addition to individual customer relationships. These incentives may lead hosts to vary their comp decisions for individual customer trips based on the extent to which they are overcomped across all customers in their portfolio. That is, hosts may face implicit pressure to reduce their comp awards to an individual customer in response to being over the comp limit of 40% at a portfolio level.

The results in column 3 show that this is the case for properties with tight monitoring but not for those with loose monitoring. The coefficient on Overcomped is positive and significant (coefficient=49.95; p<.01) while that on OvercompedxTightMonitoring is negative and significant (coefficient=-36.7; p<.01). This suggests that, in properties with loose monitoring, hosts with overcomped portfolios in the prior year continue to award higher levels of comp conditional on current and past theoretical win. In properties with tight monitoring, there is no
relationship between the customer-trip level comp decision and being overcomped at a portfolio level *per se* (coefficient for tight monitoring properties=49.95-36.7=13.25; F=1.01, p=0.32). However, the extent to which a host’s portfolio is overcomped in the prior year (*ExcessComps*) appears to influence the customer-trip level comp decision for hosts in properties with tight monitoring but not in those with loose monitoring (coefficient on *ExcessComps*=1.745, p>.10; coefficient on *ExcessCompsxTightMonitoring*=-2.635, p<.05; sum of two coefficients=-0.89; F=3.70, p=0.054). The coefficient estimates demonstrate that, on average, each 1% increase in the extent to which a host in a tight monitoring property is overcomped at a portfolio level is associated with a $0.89 decrease in the comp awarded to a particular customer on a given trip. These results provide evidence that hosts in properties with tight monitoring weight aggregate portfolio level information on their customers when making individual customer-trip comp decisions. However, this effect is relatively small. For the median theoretical win in the customer-trip level sample of approximately $700, a host in a tight monitoring property with *ExcessComps*=40 (e.g. overcomped at twice the existing guidelines) would reduce the comp percentage on an individual customer trip by only 5.1% (40*0.89/700).

In summary, the results in this section document three specific decision-making patterns which are consistent with implicit incentives from “tight” versus “loose” monitoring. First, deviation from decision-guidelines, or “experimentation”, is significantly less prevalent in properties we classify as having tight rather than loose monitoring. Second, the decisions of hosts in tight monitoring properties are less responsive to “hard information” (past customer performance) than are those of hosts in loose monitoring properties. Finally, while responding less to hard information, hosts in tight monitoring properties respond more strongly to aggregate

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8 We found similar results with an alternative, but complementary, approach of measuring – in separate regressions for tight and loose monitoring properties – the incremental variation in comp due to variation in current trip theoretical win after controlling for host and year fixed effects. Consistent with hosts in tight monitoring properties deviating less from current trip performance in their decisions, current trip theoretical win explains 39% versus 31% of the within-host and year variation in comp awards in tight versus loose monitoring properties respectively.
information on their own overall performance compared to their loosely monitored counterparts. In the next subsection, we explore the implications of these decision-making patterns for employee learning.

**Learning and the Tight vs. Loose Monitoring Effect**

Documenting learning in the decentralized information processing activities of our sample of casino hosts requires that we develop an empirical model to identify how the link between these decisions and performance outcomes varies as hosts gain experience. To the extent that hosts develop skill in incorporating unobservable (to the researcher) local information in their comp percentage decisions, these decisions should be correlated with actual realizations of future customer performance after controlling for observable historical customer performance leading to the following empirical specification:

\[
\text{TheoreticalWin}_{ijpt} = \beta_1 \text{TheoreticalWin}_{ijp,t-1} + \beta_2 \text{Comps}_{ijp,t-1} + \beta_3 \text{Comps}_{ijp,t-1} \times \text{Experience}_p + \beta_4 \text{Experience}_p + \\
+ \sum_{j=2}^{\gamma} \text{Property}_j + \sum_{t=1994}^{2003} \lambda_t \text{Year}_t + \mu_j + \epsilon_{ijpt} \quad (3)
\]

where ‘i’, ‘j’, ‘p’, and ‘t’ subscript customer, host, property, and time respectively and \( \mu_j \) denotes a host fixed effect.

Equation (3) is our basis for identifying learning in the customer management decisions of casino hosts in our research setting. If hosts are, on average, skilled at incorporating local information that is informative of future customer performance into their comp decisions, then we expect \( \beta_2 > 0 \) – hosts deviate from basing comp decisions purely on historical customer data only when future customer performance is high relative to current customer performance. If ability in acquiring and incorporating local information into comp decisions increases as hosts gain experience interacting with customers, then the relationship between these decisions and future performance outcomes should increase with experience implying \( \beta_3 > 0 \). In some of our
estimations, we will also allow the learning effect, \( \beta_1 \), to vary for properties with tight vs. loose monitoring.

We estimate equation (3) in two ways. First, we aggregate all data up to the annual host portfolio level and analyze whether hosts’ investments into their customer portfolios, in the form of comp awards, lead to increased future theoretical win at the portfolio level. This approach will allow us to capture learning effects related to managing a portfolio of customer relationships as opposed to individual customers. For this specification, we measure \( Experience \) as the number of years a host has been employed at a property at the beginning of each year. \( Comps \) and \( Experience \) are mean centered prior to interaction to maintain interpretability of coefficients. To avoid bias due to the inclusion of the lagged dependent variable, we estimate the model using the generalized method-of-moments dynamic panel data model of Arrelano and Bond (1991). The results are presented in Table 5. Consistent with the notion that hosts are, on average, skilled at incorporating local information, the estimate of \( \beta_2 \) shown in column 1 is positive and significant (coefficient=1.38; \( p<.01 \)). The coefficient estimate demonstrates that each $1 in comp invested in a host’s portfolio of customers for the year yields $1.38 of theoretical win in the next year.

The results in column 2 point to evidence of learning. The coefficient on \( Comps \times Experience \) is positive and significant (coefficient=0.043; \( p<.05 \)) consistent with the notion that hosts gain ability in acquiring and incorporating local information into their decisions as they gain experience. The coefficient estimate on \( Comps \times Experience \) documents that the “return” on each $1 in comp invested in a host’s portfolio of customers in terms of future theoretical win increases by $0.043 per year of host experience. Column (3) contains results from estimation of a version of equation (3) which allows the learning effect to vary for properties with tight vs. loose monitoring. The results show that all learning effects are
concentrated in properties with loose monitoring. The coefficient estimate on $Comps \times Experience$ in the specification in this column (coefficient=0.089; $p<.05$) captures the learning effect for loose monitoring properties. This estimate shows that the “return” on each $1 in comps invested in a host’s portfolio of customers in terms of future theoretical win increases by $0.089 per year of host experience in loose monitoring properties. The coefficient estimate on $Comps \times Experience \times TightMonitoring$ (coefficient=-0.083; $p<.05$) captures the differential learning effect for tight monitoring properties. This coefficient estimate suggests that any learning effects are essentially negated for properties with tight monitoring.

Our second approach to estimating equation (3) is to aggregate data at the customer-host-property-year level. Exploiting customer-level data allows us to use alternate measures of experience to capture different types of learning. Specifically, we estimate a version of equation (3) in which experience is decomposed into general experience ($ExpGeneral$) measured as the cumulative number of all customer-trips handled by the host up to the start of the current year and customer-specific experience ($ExpSpecific$) measured as the cumulative number of trips handled by the host for a specific customer up to start of the current year. Both types of experience may be important. Employees have multiple opportunities to learn about the performance consequences of their discretionary decisions from general experience interacting across customers, but customer heterogeneity may limit the extent to which such learning is transferable across customer relationships. Conversely, employee experience interacting with specific customers should lead directly to better discretionary decisions as employees learn about the performance consequences of their decisions for those customers.

Before turning to estimation of equation (3) using the customer level observations, we first document a simple pattern in the data that is suggestive of learning in the decentralized information processing activities of hosts. Figure 1 illustrates how a measure of the relationship
between future customer performance and current comp decisions varies with the general experience level of casino hosts. We measure the "return on comps" (ROC) for each customer-host-property-year observation as the total theoretical win for the customer at the property over the subsequent year divided by the dollar value of comps awarded to the customer by a host in the current year. To control for heterogeneity across properties and years, we then adjust this measure by subtracting its property-year level mean from each observation. We form experience portfolios by splitting the sample into 100 quantiles based on ExpGeneral and then taking the mean level of the adjusted return-on-comps measure for each portfolio. Figure 1 provides evidence consistent with learning – the ratio of future performance to the current dollar value of comps increases as hosts gain general experience interacting with customers. Hosts in the lowest experience quantiles perform significantly worse than the average for each property-year and their performance does not tend to meet or exceed property-year average performance until their experience levels are in the 10th quantile and beyond.

Table 6 contains results from estimating equation (3) using the customer-host-property-year level data. The results in column 1 provide evidence that skill in acquiring and incorporating local information into comp decisions at least partially arises via learning through general experience interacting with customers. The interaction between Comps and ExpGeneral is positive and significant at the 1% level. Consistent with the results of the host-portfolio level analyses reported in Table 5, the results in column 2 of Table 6 show that learning effects from general experience are weaker for properties with tight monitoring. The coefficient on CompsxExpGeneralxTightMonitoring is negative and significant at the 1% level.

The results in Table 6 are not consistent with learning occurring via experience interacting with specific customers (ExpSpecific). Surprisingly, the coefficient on the interaction between ExpSpecific and Comps is negative and significant at the 1% level. On average, it
appears that the quality of discretionary decisions declines as hosts gain experience with individual customers. There are at least two potential explanations for this result. First, customers may themselves be learning from repeated interaction about the organization’s comp policies. If this were the case, then customers may become more demanding of comp awards as they gain experience with a property or a specific host. In this scenario, we would expect the problem to be attenuated in properties with tight monitoring where employees are less likely to deviate from decision guidelines and exacerbated in properties with loose monitoring where employees are more likely to do so. The results in Table 6 provide mixed evidence that this is the case. The coefficient on $\text{CompsxExpSpecificxTightMonitoring}$ is positive in all specifications, but is only significant in column (3) which excludes lagged theoretical win.

The second potential explanation for the negative coefficient estimate on the interaction between $\text{ExpSpecific}$ and $\text{Comps}$ is that this result reflects the attempts of hosts to dynamically manage the cumulative comp percentage awarded to a customer over time rather than the comp percentage awarded to a customer during an individual time period (e.g. individual trip or year). If hosts overcomp a customer on one trip, they may try to recoup the "investment" by limiting comp percentages on future trips. Similarly, in managing the expectations of repeat customers, hosts may attempt to generally limit comp percentages over time. Figure 2 provides evidence that this is the case. This figure plots the cumulative comp percentage awarded by a host to a customer against the relationship-specific experience decile of the host. The cumulative comp percentage is defined for each customer-host-property-trip as the dollar value of all comps awarded to a customer by a host during all past trips divided by the total theoretical win for that customer over all past trips with the host. Relationship-specific experience deciles are formed by splitting the sample into deciles based on $\text{ExpSpecific}$ and then taking the mean level of the cumulative comp percentage for each decile. Figure 2 demonstrates that comp percentages tend
to be significantly higher during the customer’s first trip with the host, but cumulatively, the comp percentage awarded gradually converges to the 40% guideline specified in hosts’ formal decision-rights. The pattern that emerges in Figure 2 is one in which hosts dynamically manage the total comps awarded to individual customers towards the decision-guidelines prescribed by the firm.

V. Conclusion

We view our paper as among the first attempts to document the relationship between learning and management control through monitoring. We find strong learning effects in our setting which are concentrated among employees in business units that are “loosely monitored” and almost entirely absent in those that are “tightly monitored”. We also show a mechanism by which these learning effects occur. Employees in “tightly monitored” business units face implicit incentives to experiment less in their decisions leaving them fewer opportunities to learn.

In addition to the obvious caveats related to the generalizability of a field-study, we acknowledge that the proxy used in this paper to classify business units in terms of “tight” versus “loose” monitoring is based on a limited amount of data. We have attempted to combine both qualitative and quantitative data to validate our classification of business units. However, it remains for us and for future researchers to develop stronger proxies to capture variation in both the intensity and form of monitoring in organizations. Our results also speak to a tradeoff between control and learning inherent in tight monitoring but not to how this tradeoff is related to overall performance. Future research can make a contribution by identifying the long-term risk and performance implications of different monitoring choices.
References


Figure 1
Adjusted "Return-on-Comps" Across Experience Quantiles*

*Experience quantiles based on experience measured as cumulative number of trips assigned to a host; Adjusted
return-on-comps measured as $ROC_{ij} = \bar{ROC}_{ij}$ where $ROC_{ij}$ denotes return on comps for customer 'i' on trip 't' at
property 'j' and $\bar{ROC}_{ij}$ denotes the mean for $ROC_{i}^j$ across all customer-host trips in year 'y' at property 'j'.
Figure 2
Cumulative Comp Percentage across Relationship Specific Experience Deciles*

*Relationship-specific experience deciles based on experience measured as cumulative number of trips with a specific customer assigned to a host; Cumulative comp % is defined as the total dollar value of comps awarded to a customer by a host over all past trips with the customer divided by the theoretical win of that customer over all past interactions with the host.
### Table 1
Property and Host Characteristics

<table>
<thead>
<tr>
<th>properties with:</th>
<th>Tight Monitoring</th>
<th>Loose Monitoring</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Property 1</td>
<td>Property 2</td>
</tr>
<tr>
<td>Trips per Host</td>
<td>456.7</td>
<td>131</td>
</tr>
<tr>
<td>Theoretical Win Per Trip</td>
<td>1521.4</td>
<td>1058.9</td>
</tr>
<tr>
<td>Number of Unique Hosts</td>
<td>62</td>
<td>20</td>
</tr>
<tr>
<td>Number of Host-Years</td>
<td>594</td>
<td>131</td>
</tr>
<tr>
<td>Number of Host Exits</td>
<td>16</td>
<td>7</td>
</tr>
<tr>
<td>Frequency of Comp Exception Reviews</td>
<td>Daily and Monthly</td>
<td>Daily and Monthly</td>
</tr>
</tbody>
</table>
### Table 2
The Exit-Performance Relation for Properties with Tight vs. Loose Monitoring

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Dependent Variable:</strong></td>
<td><strong>EXIT</strong></td>
<td><strong>EXIT</strong></td>
</tr>
<tr>
<td><strong>Constant</strong></td>
<td>-2.726**</td>
<td>-2.612**</td>
</tr>
<tr>
<td></td>
<td>(1.15)</td>
<td>(1.15)</td>
</tr>
<tr>
<td><strong>CustomerGrowth</strong></td>
<td>-1.483***</td>
<td>-1.607***</td>
</tr>
<tr>
<td></td>
<td>(0.44)</td>
<td>(0.53)</td>
</tr>
<tr>
<td><strong>TripsPerCustomerGrowth</strong></td>
<td>0.39</td>
<td>0.377</td>
</tr>
<tr>
<td></td>
<td>(0.44)</td>
<td>(0.42)</td>
</tr>
<tr>
<td><strong>TheoreticalWinPerTrip Growth</strong></td>
<td>-0.092**</td>
<td>-0.105**</td>
</tr>
<tr>
<td></td>
<td>(0.04)</td>
<td>(0.05)</td>
</tr>
<tr>
<td><strong>Discretion %</strong></td>
<td>-2.186</td>
<td>-2.065</td>
</tr>
<tr>
<td></td>
<td>(1.53)</td>
<td>(1.47)</td>
</tr>
<tr>
<td><strong>Overcomped</strong></td>
<td>1.424***</td>
<td>1.275***</td>
</tr>
<tr>
<td></td>
<td>(0.44)</td>
<td>(0.46)</td>
</tr>
<tr>
<td><strong>ExcessComps</strong></td>
<td>0.001**</td>
<td>0.001**</td>
</tr>
<tr>
<td></td>
<td>(0.00052)</td>
<td>(0.00056)</td>
</tr>
<tr>
<td><strong>ExcessComps x TightMonitoring</strong></td>
<td></td>
<td>0.004***</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.00145)</td>
</tr>
<tr>
<td><strong>Experience</strong></td>
<td>-1.037***</td>
<td>-1.010***</td>
</tr>
<tr>
<td></td>
<td>(0.17)</td>
<td>(0.18)</td>
</tr>
</tbody>
</table>

**Implied Probabilities**

- If \( \text{Overcomped} = 0 \), and all other variables at mean
- If \( \text{Overcomped} = 1 \) and \( \text{ExcessComps} \) in 90th percentile; Loose Monitoring Property
- If \( \text{Overcomped} = 1 \) and \( \text{ExcessComps} \) in 90th percentile; Tight Monitoring Property

Standard errors in parentheses are adjusted for clustering of observations within hosts over time; * significant at 10%; ** significant at 5%; *** significant at 1%; +++ denotes jointly significant at the 1% level using \( \chi^2 \) test.

Table reports logit estimates of equation (1) using data on 1,189 host-year observations; \( \text{Exit}=1 \) if host departs from a property in the subsequent year, 0 otherwise; \( \text{CustomerGrowth} \) = annual growth in the number of customers managed by the host over the prior year; \( \text{TripsPerCustomerGrowth} \) = annual growth over the prior year in the average number of trips taken to a property by customers managed by the host; \( \text{TheoreticalWinPerTrip Growth} \) = annual growth over the prior year in the average theoretical win per trip for all customers managed by the host; \( \text{Discretion} % = \) percentage of all customer-trips managed by the host during the year in which comps were awarded in excess of 40% of the trip-level theoretical win; \( \text{Overcomped} = 1 \) if total comps awarded by the host to all customers in a given year is greater than 40% of the aggregate theoretical win across all customers managed by the host for that year.
ExcessComps = \[100\times(\text{total comps awarded by the host to all customers in a given year divided by the aggregate theoretical win across all customers managed by the host for that year})-40]\) when \(\text{Overcomped}=1\) and 0 otherwise. TightMonitoring = 1 if host is employed at properties 1, 2, or 3 and equals 0 otherwise; Experience = number of years of host experience at property as of the start of the year; Main effects of TightMonitoring controlled for via property fixed effects; Model used for estimation is:

\[
P(\text{Exit}_{jt}) = f\left(\beta_0 + \beta_1 \text{CustomerGrowth}_{jt-1} + \beta_2 \text{TripsPerCustomerGrowth}_{jt-1} + \beta_3 \text{TheoreticalWinPerTripGrowth}_{jt-1} + \beta_4 \text{Discretion}\%_{jt-1} + \beta_5 \text{Overcomped}_{jt-1} + \beta_6 \text{ExcessComps}_{jt-1} + \beta_7 \text{ExcessComps} \times \text{TightMonitoring}_{jt-1} + \beta_8 \text{Experience}_{jt-1} + \sum_{j=2}^{6} \gamma^j \text{Property}_j^p + \sum_{k=1994}^{2003} \gamma^k \text{Year}_k + \epsilon_{jt}\right)
\]
Table 3
Use of Decision-Rights for Properties with Tight vs. Loose Monitoring

<table>
<thead>
<tr>
<th>Properties with:</th>
<th>All Properties</th>
<th>Tight Monitoring</th>
<th>Loose Monitoring</th>
<th>t-test for Difference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Discretion %</td>
<td>23.7 (21.8)</td>
<td>19.6 (19.3)</td>
<td>29.2 (23.8)</td>
<td>4.43***</td>
</tr>
<tr>
<td>Overcomped</td>
<td>0.235 (0.424)</td>
<td>0.139 (0.346)</td>
<td>0.368 (0.482)</td>
<td>7.35***</td>
</tr>
<tr>
<td>Comp %</td>
<td>45.8 (1.2)</td>
<td>35.6 (1.0)</td>
<td>59.8 (1.4)</td>
<td>3.21***</td>
</tr>
</tbody>
</table>

Table reports mean for each host-year level variable across 2,251 host-year observations; Standard deviations in parentheses; *** significant at the 1% level; Discretion% = percentage of all customer-trips managed by the host during the year in which comps were awarded in excess of 40% of the trip-level theoretical win; Overcomped = 1 if total comps awarded by the host to all customers in a given year is greater than 40% of the aggregate theoretical win across all customers managed by the host for that year, 0 otherwise; Comp% = total comps awarded by the host to all customers in a given year is divided by the aggregate theoretical win across all customers managed by the host for that year.
Table 4
Determinants of the Trip-Level Comp Decision for Properties with Tight vs. Loose Monitoring

<table>
<thead>
<tr>
<th>Dependent Variable:</th>
<th>Comps</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>1</td>
</tr>
<tr>
<td>( TheoreticalWin )</td>
<td>0.218***</td>
</tr>
<tr>
<td></td>
<td>(0.002)</td>
</tr>
<tr>
<td>( TheoreticalWin \times TightMonitoring )</td>
<td>-0.061***</td>
</tr>
<tr>
<td></td>
<td>(0.005)</td>
</tr>
<tr>
<td>( LagTheoreticalWin )</td>
<td>0.011***</td>
</tr>
<tr>
<td></td>
<td>(0.001)</td>
</tr>
<tr>
<td>( LagTheoreticalWin_{t+1} \times TightMonitoring )</td>
<td>-0.007***</td>
</tr>
<tr>
<td></td>
<td>(0.002)</td>
</tr>
<tr>
<td>( Overcomped \times TightMonitoring )</td>
<td>49.951**</td>
</tr>
<tr>
<td>( Overcomped \times TightMonitoring )</td>
<td>-36.667*</td>
</tr>
<tr>
<td>( ExcessComps )</td>
<td>1.745</td>
</tr>
<tr>
<td>( ExcessComps \times TightMonitoring )</td>
<td>-2.635**</td>
</tr>
<tr>
<td>Host Fixed Effects</td>
<td>+++</td>
</tr>
<tr>
<td>Site Fixed Effects</td>
<td>+++</td>
</tr>
<tr>
<td>Year Fixed Effects</td>
<td>+++</td>
</tr>
<tr>
<td>Number of Host-Customer-Trips</td>
<td>220,223</td>
</tr>
<tr>
<td>R-Squared</td>
<td>0.41</td>
</tr>
</tbody>
</table>

Standard errors in parentheses are adjusted for clustering of observations within customers over time; * significant at 10%; ** significant at 5%; *** significant at 1%; +++ denotes jointly significant at the 1% level using \( \chi^2 \) test; Table reports OLS estimates of equation (2') using host-customer-trip level data; \( TheoreticalWin \) = theoretical win generated by the customer on the current trip; \( LagTheoreticalWin \) = cumulative theoretical win generated by the customer over the 18 months prior to the current trip start-date; \( Overcomped \) and \( ExcessComps \) are measured at the host-year level and are defined in the notes to Table 2. \( TightMonitoring \) = 1 if host is employed at properties 1, 2, or 3 and equals 0 otherwise; Main effects of \( TightMonitoring \) controlled for via property fixed effects; The baseline model used for estimation is:

\[
COMP_{ipt} = \hat{\beta}_1 TheoreticalWin_{ipt} + \hat{\beta}_2 LagTheoreticalWin_{ipt} + \sum_{j=2}^{6} \gamma^j Property_j^i + \sum_{k=1994}^{2003} \lambda^k Year_k^i + \mu_j + \epsilon_{ipt}
\]
Table 5
Learning and the Return on Comps for Properties with Tight vs. Loose Monitoring

<table>
<thead>
<tr>
<th></th>
<th>Theoretical Win</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>1</td>
</tr>
<tr>
<td><strong>Theoretical Win</strong>&lt;sub&gt;_t-1&lt;/sub&gt;</td>
<td>0.062</td>
</tr>
<tr>
<td></td>
<td>(0.045)</td>
</tr>
<tr>
<td><strong>Comps</strong>&lt;sub&gt;_t-1&lt;/sub&gt;</td>
<td>1.383***</td>
</tr>
<tr>
<td></td>
<td>(0.152)</td>
</tr>
<tr>
<td><strong>Comps</strong>&lt;sub&gt;_t-1&lt;/sub&gt;×<strong>Experience</strong>&lt;sub&gt;_t-1&lt;/sub&gt;</td>
<td>0.043**</td>
</tr>
<tr>
<td></td>
<td>(0.017)</td>
</tr>
<tr>
<td><strong>Comps</strong>&lt;sub&gt;_t-1&lt;/sub&gt;×<strong>Experience</strong>&lt;sub&gt;_t-1&lt;/sub&gt;×<strong>Tight Monitoring</strong></td>
<td>-0.083***</td>
</tr>
<tr>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Experience</strong>&lt;sub&gt;_t-1&lt;/sub&gt;</td>
<td>110.353***</td>
</tr>
<tr>
<td></td>
<td>(18.603)</td>
</tr>
<tr>
<td><strong>Year Indicators</strong></td>
<td>+++</td>
</tr>
<tr>
<td><strong>Number of Host-Years</strong></td>
<td>1,720</td>
</tr>
<tr>
<td><strong>Number of Unique Hosts</strong></td>
<td>324</td>
</tr>
</tbody>
</table>

Standard errors in parentheses are adjusted for clustering of observations within hosts over time; * significant at 10%; ** significant at 5%; *** significant at 1%; +++ denotes jointly significant at the 1% level using χ² test.

Table reports Arrelano-Bond dynamic panel data estimates of equation (3) using host-year level data; **Theoretical Win**=aggregate theoretical win across all customers managed by a host during the year; **Comps**=aggregate comps awarded by host to all customers managed by that host during the year; **Tight Monitoring**=1 if host is employed at properties 1, 2, or 3 and equals 0 otherwise; **Experience** = number of years of host experience at property as of the start of the year. The baseline model used for estimation is:

\[
\text{Theoretical Win}_{ijpt} = \beta_1 \text{Theoretical Win}_{ijp,t-1} + \beta_2 \text{Comps}_{ijp,t-1} + \beta_3 \text{Comps}_{ijp,t-1} \times \text{Experience}_{ijp} + \beta_4 \text{Experience}_{ijp} + \sum_{j=2}^{6} \gamma_j \text{Property}_{ijp} + \sum_{k=1994}^{2003} \lambda_k \text{Year}_{ijp} + \mu_j + \epsilon_{ijpt}
\]
Table 6
General and Specific Learning for Properties with Tight vs. Loose Monitoring

<table>
<thead>
<tr>
<th></th>
<th>TheoreticalWin&lt;sub&gt;τ+1&lt;/sub&gt;</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
</tr>
<tr>
<td>TheoreticalWin&lt;sub&gt;τ&lt;/sub&gt;</td>
<td>0.460***</td>
<td>0.458***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0060)</td>
<td>(0.0060)</td>
<td></td>
</tr>
<tr>
<td>Comps&lt;sub&gt;τ&lt;/sub&gt;</td>
<td>0.254***</td>
<td>0.240***</td>
<td>1.223***</td>
</tr>
<tr>
<td></td>
<td>(0.0200)</td>
<td>(0.0210)</td>
<td>(0.0200)</td>
</tr>
<tr>
<td>Comps&lt;sub&gt;τ&lt;/sub&gt; x ExpGeneral</td>
<td>0.0004***</td>
<td>0.0006***</td>
<td>0.002***</td>
</tr>
<tr>
<td></td>
<td>(0.0001)</td>
<td>(0.0002)</td>
<td>(0.0002)</td>
</tr>
<tr>
<td>Comps&lt;sub&gt;τ&lt;/sub&gt; x ExpSpecific</td>
<td>-0.003***</td>
<td>-0.003***</td>
<td>-0.007***</td>
</tr>
<tr>
<td></td>
<td>(0.0010)</td>
<td>(0.0010)</td>
<td>(0.0010)</td>
</tr>
<tr>
<td>Comps&lt;sub&gt;τ&lt;/sub&gt; x ExpGeneral x TightMonitoring</td>
<td>-0.001***</td>
<td>-0.003***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0003)</td>
<td>(0.0003)</td>
<td></td>
</tr>
<tr>
<td>Comps&lt;sub&gt;τ&lt;/sub&gt; x ExpSpecific x TightMonitoring</td>
<td>0.0001</td>
<td>0.003**</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0010)</td>
<td>(0.0010)</td>
<td></td>
</tr>
<tr>
<td>ExpGeneral</td>
<td>4.757***</td>
<td>4.857***</td>
<td>7.132***</td>
</tr>
<tr>
<td></td>
<td>(0.2810)</td>
<td>(0.2840)</td>
<td>(0.3390)</td>
</tr>
<tr>
<td>ExpSpecific</td>
<td>27.910***</td>
<td>27.698***</td>
<td>51.718***</td>
</tr>
<tr>
<td></td>
<td>(1.5980)</td>
<td>(1.6000)</td>
<td>(2.2840)</td>
</tr>
<tr>
<td>Host Fixed Effects</td>
<td>+++</td>
<td>+++</td>
<td>+++</td>
</tr>
<tr>
<td>Site Fixed Effects</td>
<td>+++</td>
<td>+++</td>
<td>+++</td>
</tr>
<tr>
<td>Year Fixed Effects</td>
<td>+++</td>
<td>+++</td>
<td>+++</td>
</tr>
<tr>
<td>Observations</td>
<td>229,861</td>
<td>229,861</td>
<td>229,861</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.34</td>
<td>0.34</td>
<td>0.25</td>
</tr>
</tbody>
</table>

Standard errors in parentheses are adjusted for clustering of observations within customers over time; * significant at 10%; ** significant at 5%; *** significant at 1%; +++ denotes jointly significant at the 1% level using $\chi^2$ test; Table reports OLS estimates of equation (4) using customer-host-year level data; TheoreticalWin=customer’s total theoretical win during the year; Comps=total comps awarded by the host to the customer during the year; ExpGeneral=Cumulative number of trips managed by the host up to the start of the year; ExpSpecific=Cumulative number of trips for a specific customer managed by the host up to the start of the year; TightMonitoring=1 if host is employed at properties 1, 2, or 3 and equals 0 otherwise. Note that the estimates provided in column 3 of Table 6 exclude lagged theoretical win. The reason we include this column is to check whether the relatively low baseline “return on comps” (e.g. coefficient on lagged theoretical win) reported in columns 1 and 2 is an artifact of aggregating the data at the customer-year level. If comps awarded during the current year are associated with a persistent increase in theoretical win that arises later in the same year for a given customer (e.g. from repeat trips within the year), then this portion of the “return on comps” would be obscured by the inclusion of lagged theoretical win (particularly when current and lagged theoretical win are correlated as is clearly the case given the coefficients on lagged theoretical win in columns 1 and 2). The results in column 3 suggest that this is indeed the case as the baseline “return on comps” rises to approximately $1.22 in the absence of lagged theoretical win as an additional explanatory variable: Baseline model tested is:

$$
\text{TheoreticalWin}_{ijpt} = \beta_1 \text{TheoreticalWin}_{ijp,t-1} + \beta_2 \text{Comps}_{ijp,t-1} + \beta_3 \text{Comps}_{ijp,t-1} \times \text{ExpGeneral}_{ij} + \beta_4 \text{Comps}_{ijp,t-1} \times \text{ExpSpecific}_{ij} + \beta_5 \text{ExpGeneral}_{ij} + \beta_6 \text{ExpSpecific}_{ij} + \sum_{j=2}^{k} \gamma_j \text{Property}_{ij} + \sum_{k=1994}^{2003} \lambda_k \text{Year}_{ij} + \mu_j + \epsilon_{ijp}
$$