Bending the Cost Curve Through Employee Learning

Ranjani Krishnan
Michigan State University

Hari Ramasubramanian
Michigan State University

ABSTRACT

We examine factors that influence employee learning. Learning curve theory predicts that as employees learn on the job, costs are a function of *accumulated* volume, not just output rate. Thus, the short-run output decision becomes an investment decision with a longer horizon in the presence of learning curves. Using data from clinical laboratories, we find theory-consistent evidence of autonomous learning by technical and supervisory labor, which manifests as a non-linear reduction of labor hours and labor cost when cumulative volume increases. Our results indicate that clinical labs engage in a quality-cost tradeoff for technical labor. Labs belonging to lower quality hospitals exhibit greater cost reduction through learning relative to their higher quality counterparts. We find that for-profit labs have less favorable learning curves for technical labor. Labs belonging to hospitals that have higher technical efficiency have more favorable learning curves. Our study contributes to the understanding of how employee learning can influence cost behavior in various types of organizations and helps to unpack the micro-foundations of cost management.

Keywords: Learning Curve, Cost Management, Employee Learning, Cost-Quality Tradeoffs.

JEL Classifications: D02; M21; M41

This paper has benefited from the suggestions of Susanna Gallani, Martin Holzhacker, Satish Joshi, Jeffrey Wooldridge, and workshop participants at Michigan State University, Iowa State University, and the 2020 AAA MAS meeting.

Bending the Cost Curve Through Employee Learning

1. Introduction

In 1968, BCG emphasized the long-term competitive gains that accrue to firms that make use of the learning curve (Henderson 1968). Fifty years later, BCG reiterated that organizations with ability to learn obtain enduring competitive advantage (Reeves, Stalk, Pasini 2013). The learning curve refers to the empirical observation that cost per unit follows a pattern of decrease as employees' cumulative experience increases. Simply stated, employees get better at a given task when they perform it more often. Economists such as Arrow (1962), Lucas (1988), and Krugman (1987) have shown the beneficial effects of learning curve on productivity growth. At the firm level, employee learning can create barriers to entry, offer protection from competition, be a source of competitive advantage (Ghemawat and Spence 1985; Spence 1981), and serve as a reliable mechanism to achieve long-term cost reductions (Thompson, 2012). In this paper, we examine the effect of learning by direct labor and supervisory employees on cost behavior. We analyze whether contextual factors such as quality culture, ownership status, and technical efficiency influence the extent of learning.[1]

The learning effect on cost occurs from numerous factors, the most prominent of which are employee skill, knowledge assimilation, and peer collaborations. Skill theory posits that as individuals accumulate task experience, they experiment with different combinations of activities and efforts, retain the successful ones, and discard the unsuccessful ones (Crossman 1959). With experience, employees also obtain deeper content knowledge, which increases task efficiency and effectiveness. Knowledge assimilation occurs with experience, whereby employees develop an ability to apply logic that was used to solve a particular problem to other situations, increasing the overall understanding of a problem domain (Kim et al. 2012). Learning from peers enables

[1] A firm is said to be technically efficient if it maximizes the output from a given level of inputs or minimizes the inputs to produce a given level of output (Debreu 1951).

the transfer of tacit knowledge with attendant advantages to learning curves throughout the organization (Argote 2013; Kelsey et al. 1984).[2] Successful organizations institutionalize this tacit knowledge and embed them into routines enabling multi-level learning across units. Although learning accrues as a function of volume, the learning effect on cost is theoretically and empirically different from scale economies. The effect of learning on costs occurs from *accumulated volume,* whereas the effect of economies of scale occurs from the *output rate* (Spence 1981). Learning has implications for managerial decisions and resource strategies. Managers must first notice the investment opportunity that is provided by learning and make output decisions that incorporate accumulated volume. Second, they must commit resources to learning by focusing on cumulative output rather than short-term output.

Learning can either be autonomous or induced from elements within and outside the organization (Dutton and Thomas 1984). Autonomous learning occurs on the job, and is often referred to as "learning-by-doing" (Adler and Clark 1991). Autonomous learning yields productivity improvements from task repetition and experience. Various elements can influence autonomous learning. These can be firm-specific (such as organizational structure, employee turnover, or technological adoption), market-specific (such as the rate of technological change or competition), or environmental (such as natural disasters) (Anderson and Lewis 2014).

Managers' resource decisions determine whether organizations can successfully exploit the benefits of learning curves. Management accountants have an important role to play in the calibration of learning curves, and incorporation of the results into the planning, forecasting, and budgeting cycles. Notwithstanding the practical relevance of learning curves, extant accounting research on this topic is sparse. Analysis of learning curves requires task-level data, which is difficult to obtain. A few studies use field data to demonstrate the existence of learning curves

[2] Tacit knowledge is difficult to articulate and includes technical skills which are hard to formalize but can be learned from observing the person possessing such knowledge (Nonaka and Takeuchi 1995).

(Argote and Epple 1990; Wiersma 2007). While these studies make valuable contributions, they do not examine variations in learning curves across organizations. We use archival task-level data from clinical labs for our analysis. Clinical lab tasks are narrow in focus, repetitive, and labor oriented, which is an ideal setting to empirically examine the effect of learning on cost behavior. Furthermore, clinical labs are an integral part of the health care system.

Clinical labs conduct screening, monitoring, and diagnostic testing using bodily fluids. An average of 7 billion clinical lab tests are performed each year within the U.S. Clinical lab tasks occur in three stages (Travers and Krochmal 1988). These include, the pre-analytic stage (prepping the patient and the test, collecting the specimen, transporting the specimen), the analytic stage (testing of the specimen, preparing reports), and the post-analytic stage (interpreting the results). Labs are required to follow strict protocols, both with respect to inputs (materials, labor, and equipment) and processes. There are standardized operating procedures at each stage of lab testing, which eliminates process variations across employees. Despite these input and process controls, lab testing errors are among the most commonly occurring medical errors (Fernald et al. 2004; West et al. 2009).

We examine three contextual factors that can affect learning – quality culture, ownership status, and technical efficiency. With respect to *quality culture*, we examine whether labs make cost-quality tradeoffs. Operational improvements such as standardized process pathways have the potential to reduce cost as well as improve quality (IOM 2001). However, labs that have a cost-culture could make cost improvements at the expense of quality improvements (Jha et al. 2009; Yasaitis et al, 2009), especially given that lab services are reimbursed based on a fixed-fee per test. We examine two commonly used measures of clinical quality (Lingsma et al. 2018), namely mortality and average length of stay (LOS) for the associated hospital. If a quality-cost tradeoff exists, labs in low-quality hospitals would have better learning curves than labs in high-quality hospitals. With respect to *ownership status*, we expect labs belonging to for-profit

hospitals to have worse learning curves than non-profit and government hospitals. For-profit hospitals are owned by physician groups or corporations. Relative to non-profits, for-profit hospitals pay lower wages and benefits to technical employees and encounter higher staff turnover (Alexander et al. 1994; O'Brien-Pallas et al. 2006; Mukamel et al. 2009; Shen 2003), which adversely affect learning curves. With respect to *technical efficiency*, we expect that hospitals with higher technical efficiency will have more favorable learning curves. Technically efficient hospitals tend to have routines and capabilities for better exploitation of knowledge (Ding 2014), which would permeate into laboratory learning curves.

Our empirical analysis uses data on clinical lab tests from California hospitals for the period 1997−2015. We analyze several types of labor time and cost including: (a) technical hours per unit, (b) technical wages per unit, (c) supervision hours per unit, and (d) supervision wages per unit. We find robust evidence of learning effects for technical and supervisory labor time and cost, ranging from an 84% to an 88% learning curve.[3] Low quality hospitals i.e., hospitals with higher mortality rates have more favorable learning curves for technical labor, suggesting that a cost-quality tradeoff exists. This cost-quality tradeoff also occurs within hospitals. For example, when hospitals focus on increasing quality by increasing LOS, learning curves for lab technical labor become less favorable. For-profit labs have less favorable technical labor learning curves, indicating that these hospitals are likely to have a short-term orientation towards cost-reduction compared to non-profit and government hospitals. Hospitals that are at or above the mean level of technical efficiency have more favorable technical labor learning curves, indicating that the overall technical efficiency of the hospital spills over into learning rates for technical labor.

We make several contributions to the accounting literature. First, despite widespread acceptance in theory (Spence 1981; Lieberman 1984; Ghemawat and Spence 1985; Grosse et al.

[3] An 88% learning curve indicates a reduction of 12% in technical labor cost per unit when cumulative lab tests double.

2015; Glock et al. 2019) and practice (Steven 2010), limited research in accounting examines the effect of learning curves on cost functions. Learning curves are a staple of the cost accounting curriculum throughout the world (Datar and Rajan 2017). Although a wealth of accounting research examines cost behavior with respect to volume (Banker and Byzalov 2014; Banker et al. 2018), the focus has been on the causes and consequences of *nonlinearities* in short-term cost, such as cost stickiness.[4] Our focus is on the effect of employee learning as a mechanism for long-term cost *reduction*, with attendant implications for budgeting, forecasting, and performance measurement. We add to the accounting literature by identifying employee learning as a source of cost non-linearity.

Second, we address the call in the recent cost management literature to open the black box of cost behavior (Banker et al. 2018). To our knowledge, ours is the first study to calibrate the impact of employee learning on labor hours, labor cost, and direct cost using data at the *task* level. Prior cost behavior research has focused on aggregate cost pools such as SGA or operating costs. While these studies have made substantial contributions to accounting research and practice, the theoretical underpinnings of cost behavior as well as examination of micro-evidence is sparse. Our analysis contributes to the understanding of the micro-foundations of cost behavior and unpacks the theoretical drivers of cost.

Third, a deeper understanding of the micro-foundations of cost behavior can inform managerial decision making with respect to human resource (HR) strategy and job design. Improving employee work processes, and designing HR strategies to recruit, train, and retain employees can have major implications for cost behavior. Wiersma (2007) finds that learning is enhanced when employees have some degree of slack resources, which provide opportunities for experimentation. Our study extends Wiersma (2007) by showing that quality culture, ownership

[4] Cost stickiness refers to a smaller reduction in costs for a sales decrease than an increase in costs for an equivalent sales increase (Anderson, Banker, and Janakiraman 2003).

status, and technical efficiency influence employee learning. In additional analysis, we show that task scope enhances learning curves, which has implications for organizational structure and job design.

Finally, we contribute to the healthcare literature. The debate about the extent of healthcare spending in the US, which was $3.8 trillion in 2019 (comprising 17.7% of the GDP),[5] has focused on healthcare "value" defined as health outcomes achieved per dollar spent (Porter and Teisberg 2006). We identify employee learning as a cost reduction mechanism that can enhance healthcare value.

Section 2 provides contextual information related to clinical laboratories, discusses theories on learning curves that explain individual and organizational learning, and presents the hypotheses. Section 3 discusses the data, variable measurement and models. Section 4 presents the results, Section 5 tests the robustness and describes the economic significance of the results and Section 6 concludes.

2. Institutional Setting, Theory, and Hypotheses

Institutional Setting

The U.S. clinical lab industry generates about $100 billion in annual revenues, employs over 620,000 people, and accounts for about 2% of total healthcare costs (ACLA 2017). Laboratory tests are crucial at all stages of medical care including diagnosis, treatment, follow-up care, and preventative care. Physicians and staff order clinical lab tests for approximately 98% of inpatients and 29% of outpatients (Ngo, Gandhi, and Miller 2017). Clinical labs can be hospital-based, independent (e.g. Quest Diagnostics), or located in physician offices. About 55% of all medical lab tests are conducted in hospital-based labs, which is the focus of this research. Hospital-based

[5] https://www.cms.gov/Research-Statistics-Data-and-Systems/Statistics-Trends-and-Reports/NationalHealthExpendData/NationalHealthAccountsProjected.

labs are managed as responsibility centers. The overall strategy of the hospital influences the strategy of the medical lab and as such there is no independent theory of the medical lab that is different from the hospital as an organization. Therefore, in this section, we assume that hospital strategy and operations have direct implications for the lab.

The task process in clinical labs begins when a specimen is collected from a patient. The lab technician ascertains that the specimen is appropriate for the medical test and sends it to the medical lab where scientific testing occurs, and results are recorded. Results are then transmitted to the physician, who makes a diagnosis. Lab testing involves considerable labor at each stage. At the pre-analytic stage, a lab technician prepares the patient and collects the specimen. Although some labs may have pneumatic delivery systems, the delivery of the specimen to the lab also occurs manually in most labs. At the analytic stage, a lab technician processes the specimen and uses tests and equipment to generate test results. The lab technician must first determine that the test was properly conducted before forwarding the results to the physician for the post-analytic stage. Results that are positive for a disease or a medical condition are frequently re-analyzed to reduce false positives. Most clinical labs employ licensed, highly skilled staff. Lab technicians usually have a baccalaureate degree from an accredited laboratory science program and must pass a certification exam from the American Society for Clinical Pathology (ASCP). Effectiveness on the task requires technical knowledge that goes beyond simple biology (e.g., a lab technician may have knowledge about how to draw blood from an average patient, but may struggle with patients whose veins are hard to find), practical knowledge (e.g., which test tube to use and where to store), and problem solving knowledge (e.g., dealing with excessive bleeding at test site). Therefore, learning is an important driver of cost efficiency for clinical lab tasks. The following section briefly reviews the literature on learning curves, with specific reference to health care.

Theory

Learning curves and cost functions

The learning curve refers to the decline in unit costs of production at a decreasing rate as accumulated output increases (Spence 1981). Empirical research has found evidence of learning curves in a variety of industries, including job costing settings, such as aircraft manufacturing (Wright 1936; Benkard 2000), ships (Rapping 1965), and technology support (Kim et al. 2012), and process costing settings such as petroleum (Hirschmann 1964) and chemicals (Lieberman 1984). Learning curves are particularly salient in industries such as health care where the tasks are repetitive either by design or due to regulation that requires process control protocols. Learning influences cost behavior in two ways – first, it reduces labor cost per unit as a function of cumulative output, and second, it introduces non-linearity into cost functions. Learning curves can influence long-term competitive advantage by creating entry barriers and protection from competition with substantial impacts on market shares and profitability, over and beyond that provided by scale economies (Ghemawat and Spence 1985; Amit 1986).

Learning curve effects on cost behavior are well grounded in theory and prevalent in practice; nevertheless, accounting research on learning curves is sparse. A wealth of research in accounting research on cost behavior focuses on non-linearities in the relationship between cost behavior and volume using aggregate cost pools (such as SGA, Operating costs, COGS) and short run costs. Beginning with the seminal work of Anderson et al. (2003), robust evidence demonstrates a nonlinear behavior of cost with respect to volume. Evidence suggests that in many industries, major cost categories exhibit stickiness, i.e., the decrease in cost for a decrease in sales volume is lower than an increase in cost for an increase in sales volume. This asymmetric behavior has been attributed to resource procurement decisions of managers (Banker and Byzalov 2014). When volume decreases, managers are reluctant to relinquish unused resources to avoid future resource adjustment costs. When volume increases, managers are more inclined to add

requisite resources (Banker et al. 2018). Accounting research has not studied the nonlinearities that are introduced into cost function because of employee learning, and the contextual factors that determine the extent of learning. An exception is Wiersma (2007) who uses three years of monthly field data from the Royal Dutch Mail and shows that learning curves are more favorable when there are a moderate number of temporary employees, greater number of related tasks, greater availability of slack in resources, and absence of other performance dimensions on cost. Managerial decisions including resource choices influence learning curves. When there is potential for learning curves, managers must approach the short-run output decision as an investment decision and commit resources to accumulating output through employee experience (Spence 1981).

Factors influencing learning

We first examine the extent of learning in clinical labs. Next, we examine three contextual factors that influence the extent of learning. These include cost-quality tradeoffs, ownership, and technical efficiency.

Hypotheses Development

Autonomous Learning or Learning by Doing

Research in organizational learning attests the beneficial effect of repeated task execution on learning curves (e.g., Yelle 1979; Epple et al. 1996; Boone et al. 2008; Zollo and Winter 2002). Learning does not occur when managers simply hire employees and assign tasks. Managers must understand how learning occurs and invest in employee learning. Managerial decisions that influence learning include job design, production techniques, operating protocols, and process controls.

Autonomous learning is affected by individual characteristics as well as the properties of the task. Learning can also spill over across tasks. Mukhopadhya et al. (2011) examine learning in the setting of IT-enabled physician referral systems (IT-PRS) and find significant learning

spillovers across task types. Learning can increase explicit knowledge (that can be articulated) or tacit knowledge (that is difficult to articulate) (Schilling et al. 2003). Knowledge accumulation through repeated task execution enables the formation of learning routines that enable the benefits of learning to accrue and grow, even if these routines are not formalized or articulated.

Certain types of tasks have greater amenability to learning by doing. Such tasks are usually repetitive, labor oriented, and have a low technology content. These tasks can span mature process technologies; that is, learning does not only occur for tasks that are at early stages of development (Wiersma 2007). Clinical laboratory testing is an example of a task that is amenable to learning by doing. Clinical lab tests require a standardized structure and pre-determined process routines. As employees obtain task experience on lab testing, their knowledge becomes embedded into routines and contributes to learning (Rerup and Feldman 2011), which increases tacit knowledge (Cyert and March 1963; March and Simon 1958). Accordingly, we expect that clinical lab testing, which is characterized by execution of procedures and routines formed from repetitive patterns of activity, will exhibit learning curves that reduce costs. This leads to the following hypothesis:

HYPOTHESIS 1. *The average cumulative direct cost per unit reduces with an increase in cumulative clinical lab tests.*

Cost-Quality Tradeoffs in Autonomous Learning

Healthcare quality has been a topic of extensive policy debate particularly since the publication of the report "To Err is Human" by the Institute of Medicine in 1999. This report provided evidence that hospital errors were the third leading cause of death in the U.S. with 98,000 patient deaths each year from preventable medical errors. Quality is an important factor that prominently features in hospital decision making. Hospitals invest in infrastructure, employees, and control systems to improve quality of care. Although quality investments are expensive and may involve tradeoffs between quality and cost, there is mixed evidence about whether such a tradeoff

between quality and cost even exists. On the one hand, some argue that hospitals with lower cost could be better managed and have higher quality of care (Deily and McKay 2006), while others find that high-cost hospitals provide better quality care (Stukel et al. 2012). A study by Jha et al. (2009) finds worse quality outcomes for common medical conditions in low-cost hospitals.

The quality-cost tradeoff is particularly pronounced in services where there is a direct and visible tradeoff between increasing the quantity of patients serviced and quality of care and where revenue is based on a fixed-fee per unit (Grieco and McDevitt 2017). For example, a lab can perform more tests if it tightly schedules patients, minimizes time per patient, and spends less time cleaning equipment and workspaces after each test. All these steps improve learning rates but can be detrimental to quality.

A hospital that has quality as an integral part of its competitive strategy is likely to align its organizational control systems and processes to ensure success of its quality strategy (Ittner and Larcker 1997). A quality-focused hospital will be ready to alter or change protocols or clinical pathways to improve patient quality outcomes. When quality problems occur, a quality-focused hospital would invest in considerable off-line analysis to identify the root causes of quality problems and explore solutions (Levin 2000). Additionally, it's labor policy will focus on retention of qualified employees rather than cheaper employees; therefore, it would be reluctant to cut labor costs. Conversely, a hospital with a cost focus will be reticent to change processes if such a change adversely affects costs. For a cost-focused hospital, quality improvement policies have the risk of shifting employee focus away from cost reduction with adverse implications to its cost function. A cost-focused organization is likely to view employee costs as a target area for cost reduction and impose greater cost targets to speed up employee learning. We expect that a hospital with poorer quality of care have more favorable learning curves.

HYPOTHESIS 2. *Clinical labs located in hospitals that have poorer quality of care will have more favorable learning curves.*

Hospital Ownership and Learning Curves

Literature posits that organizational factors influence learning (Argote 2013). An important organizational context that influences the way in which work occurs is hospital ownership structure. While prior research in healthcare finds differences in cost as a function of ownership type (Becker and Sloan 1985; Valdmanis 1990; Lee et al. 2009), these differences are difficult to interpret because of heterogeneity of services across ownership types (Carter et al. 1997). An advantage of our setting is that we examine a homogenous task, which provides an opportunity to test differences in learning curves across hospitals by ownership structure. We examine the difference in learning rates between for-profit and nonprofit and government hospitals.

For-profit hospitals emphasize cost consciousness and operational discipline to improve profitability (Andreasen et al. 2008) whereas non-profit hospitals focus on breaking even (Kumar et al. 1998). Relative to non-profits, for-profit hospitals have lower employee benefits such as pensions, paid leave, and part-time work options (O'Brien-Pallas et al. 2006). For-profit hospitals use incentive compensation tied to financial performance measures (Tiemann et al. 2012), while incentive pay is uncommon in nonprofit hospitals and not used at all in government hospitals. Non-profit and government hospitals have a non-distribution constraint and do not have shareholders or owners (Newhouse 1970; Fama and Jensen 1983; Hansmann 1980). For-profit hospitals, on the other hand, are monitored by shareholders or private owners. Thus, for-profit hospitals are more sensitive to the preferences of the capital market and likely to focus on continuous cost control. For-profits are more likely to make greater use of temporary employees and use short-term labor contracts.

The effectiveness of learning curves requires a long-term orientation and a focus on building long-term knowledge capital; therefore, for-profits are likely to have lower learning rates. Additionally, non-profit hospitals and government hospitals usually have a larger range of services offered, which increases their absorptive capacity whereby they can assimilate

information more effectively (Cohen and Levinthal 1990). Employees in non-profit hospitals receive non-pecuniary compensation such as flex-time and enjoy better relationships with stakeholders such as staff and the local community (Becchetti et al. 2013). Labor turnover is accordingly lower in non-profit hospitals than for-profit hospitals (Alexander et al. 1994; Mukamel et al. 2009). Therefore, we posit that labs located in for-profit hospitals will have less favorable learning curves than non-profit and government hospitals.

HYPOTHESIS 3. *For-profit labs have less favorable learning rates relative to non-profit and government labs.*

Technical Efficiency and Learning Curves

Technical efficiency refers to the extent of inputs required to produce a certain set of outputs (Leibenstein 1966). Technical efficiency permeates all aspects of a hospital's production function. Factors that promote technical efficiency include effective application of new technologies and organizational systems, standardization without sacrificing flexibility and adaptability, continuous improvements in value-chain processes such as materials and labor flows, appropriate division of labor, and coordination throughout the supply chain (Epple et al. 1991; Joskow and Rose 1985). Organizations that continually identify, adopt, and share best practices have higher long run technical efficiency (Ding 2014). Such organizations are also likely to be more effective in encouraging employee learning that becomes embodied within the organization and transfers from one organizational context to another.

The Agency for Healthcare Research and Quality (AHRQ) defines efficiency as maximization of output with a given set of inputs (McGlynn et al. 2008; Ding 2014). For a given sum of outputs, hospitals that require relatively fewer inputs are more technically efficient than hospitals that require more inputs. We use this definition to examine the relationship between technical efficiency and learning curves. Learning curves result in a lower level of inputs to produce a given quantity of output and embody the definition of technical efficiency.

Consequently, we posit that labs belonging to hospitals with high overall technical efficiency will have more favorable learning curves.

HYPOTHESIS 4. *Relative to labs belonging to hospitals with lower technical efficiency, labs belonging to hospitals with higher technical efficiency will have more favorable learning rates.*

3. Data, Variable Measurement and Methodology

Data

Our analyses span the period 1997-2015. We select 1997 as the start date because of two reasons. First, in the 1980s several health care pricing regulation programs were implemented. A prominent regulation was the prospective payment system (PPS), implemented in 1983, which changed the reimbursement system for Medicare inpatients from cost-based reimbursement to fixed fee. The PPS was subsequently extended to outpatient and ancillary services in the mid-90s. By 1997, hospital reimbursement for all Medicare and Medicaid services had transitioned to a fixed fee. Second, by 1997, the gap between public insurance programs (such as Medicare and Medicaid), and private insurance programs had reduced, with many private insurance programs adopting Medicare type fixed fee systems (Sood et al. 2013; Tompkins et al. 2006). We end at 2015, which is the most recent year for which audited data is available.

We use data on clinical lab tests for California hospitals from the Hospital Annual Financial Disclosure Report database of the Office of State Health Planning and Development (OSHPD). This report contains annual data on all medical services provided by the hospital. We manually extract the data for clinical labs for each year and append them across years. We deflate all financial data (including wages) by the Consumer Price Index (CPI) obtained from Bureau of Labor Statistics. The dataset covers 446 to 520 hospital-based labs across years resulting in 8,754 lab-year observations. We restrict the sample to only include hospitals with clinical lab information during the sample period. Our final dataset consists of an unbalanced panel of 5,054 lab-year observations for 211 to 297 labs across years. Table 1 provides a breakdown of

observations by year used in the analyses. Appendix A contains variable definitions. Appendix B contains the location in the OSHPD database for each variable.

– Insert Table 1 here –

Variable Measurement

Dependent Variables

Technical Hours per Unit and Technical Wages per Unit

Technical hours per unit is the natural log of cumulative hours worked by lab technicians in a clinical lab up to and including year *t*, divided by the cumulative number of clinical tests conducted by the lab up to and including year *t*. *Technical wages* per unit is the natural log of the sum up to and including year *t* of the product of technical hours worked by lab technicians in a clinical lab and the deflated average hourly wage rate for lab technicians divided by the cumulative number of clinical tests conducted by the lab up to and including year *t*.

Supervision Hours per Unit and Supervision Wages per Unit

Supervision hours per unit is the natural log of cumulative hours worked by managers and supervisors in a clinical lab up to and including year *t*, divided by the cumulative number of clinical tests conducted by the lab up to and including year *t*. *Supervision wages* per unit is the natural log of sum up to and including year *t* of the product of supervision hours in a clinical lab and the average deflated hourly wage rate for lab supervisors divided by the cumulative number of clinical tests conducted by that lab up to and including year *t*.

Salary per Unit

While technician wages allow for estimation of learning curves at the direct labor cost level, they do not capture productivity gains that accrues in *indirect* labor cost pools from learning curves (Wiersma 2007). Therefore, we also estimate learning curve effects for the aggregate pool of all the employees working in the clinical lab. This variable is the natural log of deflated total salaries

and wages incurred by a clinical lab up to and including year *t* divided by the cumulative number of clinical tests conducted by that lab up to and including year *t*.

Direct Cost Per Unit

Direct cost is the natural log of cumulative deflated direct expenses of a clinical lab up to and including year *t* divided by the cumulative number of clinical tests conducted by that lab up to and including year *t*. Consistent with hospital reporting protocols, lab direct expenses include lab-specific overheads and measure the full cost of a lab, excluding allocated hospital-level overheads.

Independent Variables

Cumulative Units

This is measured for each clinical lab as:

$$\text{Cumulative units}_{\text{t}} = \log(\sum_{n=1}^{t-1} Number\ of\ clinical\ tests)$$

Economies of Scale

The effect of learning curve on the cost function is independent of economies of scale. Learning curve theory examines the effect of *accumulated volume* and not *output rate*. Economies of scale refer to the decline in average costs as a function of output rate, which can co-exist with learning (Spence 1981). It is important to separate economies of scale from learning effects (Berndt 1991; Campbell et al. 2011; Pisano et al. 2001). Operationally, economies of scale occur as a reduction in unit cost due to an increased production at a point in time. We measure economies of scale by the natural logarithm of clinical tests conducted by a clinical lab in the current year i.e., year *t*. Figure 1 shows how learning and scale economies together can reduce cost per unit. Economies of scale lead to a movement along the average cost curve (Change from A to B) whereas learning curves involve a shift in average cost curve (Change from A to C).

– Insert Figure 1 here –

Low-Quality Hospital

We measure output as well as process quality. For output quality, we use mortality rates (Holt et al. 2010; Lingsma et al. 2018; Stelfox and Straus 2013). We include an indicator variable (*Low quality hospital*) equal to one if the average mortality rate for the hospital where the lab exists is above the median mortality rate for all hospitals during the sample period and zero otherwise.

We use length of stay (LOS) as a process measure of quality. Higher LOS indicates greater resource use. Discharging patients earlier reduces resource use but leads to greater complications that occur after discharge. We compute *Average length of stay (LOS)* as the natural logarithm of total patient days divided by total discharges in the current year for the hospital where the lab is situated. For comparability across hospitals, we exclude long term care patient days while computing LOS because not all hospitals provide long term care.

For-Profit Hospital

We include an indicator equal to one if the hospital is a for-profit hospital and zero otherwise.

High Technical Efficiency Hospital

Technical efficiency refers to how efficiently an organization converts inputs into outputs. We measure technical efficiency at the hospital level using Data Envelopment Analysis (DEA). We use the logarithm of net patient revenue as the output and three inputs that capture labor, operating processes, and capital. These inputs are logarithm of hospital full-time equivalent employees, logarithm of operating expenses, and logarithm of total assets. We aggregate these variables for each hospital over the sample period and construct technical efficiency scores. *High technical efficiency hospital* variable equals one if the technical efficiency score for the hospital is equal to or above the mean technical efficiency score for the entire sample and zero otherwise.[6]

[6] DEA is a non-parametric approach and makes fewer assumptions than Stochastic Frontier Analysis (SFA) which is an alternative method to measure efficiency. We prefer DEA because it measures efficiency relative to other hospitals in the sample and assumes any departure from efficient frontier as inefficient.

Lab Employee Intensity

We control for lab employee intensity as natural logarithm of productive hours worked by technical and specialist employees in the clinical lab divided by gross patient revenue generated by the clinical lab. Higher the lab employee intensity, the greater the productive hours required for each dollar of lab revenue generated.

Lab Importance

We include a control variable that measures the importance of the lab for the hospital. This variable is measured as the natural logarithm of productive hours worked by technical and specialist employees in the clinical lab divided by total productive hours worked by all the technical and specialist employees in the hospital where the lab is situated.

Depreciation

We control for the level of capital investments by including the natural logarithm of depreciation cost for assets belonging to clinical labs. We do not deflate the depreciation by CPI because depreciation is computed on historical cost and not affected by inflation.

Outsourcing

We control for the extent of outsourcing of lab services, defined as purchased services as a percentage of direct clinical lab expenses (Balakrishnan et al. 2010).

Methods

The standard model to describe the learning curve is $AC = ax^{-b}$ where b is the learning rate or learning index and a is the number of labor hours or cost of producing the first unit and AC is the cumulative average cost (or cumulative hours per unit) of producing x units (Wright 1936). There are two broad potential specifications of the learning curve – the Crawford (1944) model and the Wright (1936) model. The Crawford model assumes that *unit cost* decreases by a constant percentage as the quantity of units is doubled, while the Wright model assumes that the *cumulative average cost* decreases by a constant percentage as the total quantity of units produced

doubles. The cumulative average formulation proposed by Wright (1936) is more appropriate in our setting for the following reasons. First, the Wright model is suitable in production environments where, although infrastructure exists, changes are expected over time. As opposed to this, the Crawford model assumes that hospitals have a stable lab infrastructure. In our setting, although most hospitals have lab testing activity, changes to the organizational structure and routines are commonplace. Lab testing is often designed as a modular activity in hospitals where changes, such as whether to employ own labor or outsourced labor (agency workers), or whether to use own or leased equipment are common. Thus, there are differences in the level of maturity in various production cycles, which introduces random error in the Crawford model. By averaging production costs, the Wright model smooths out cost variations and yields a more precise estimation. Second, the Crawford model is more sensitive to the choice of a specific time interval than the Wright model. Third, the Wright model is more suitable when cost based learning involves tradeoffs between cost efficiencies and quality improvements because accommodating such tradeoffs in organizational routines will introduce cost variations.[7,8] Finally, the Wright model has been found to be the most suitable to represent learning curves in field and simulation research (Grosse et al. 2015).

One concern with Wright model is the presence of serial correlation because if the cost in a particular year is high it will be correlated with costs in future years due to accumulation of costs across periods. An advantage of panel data with a relatively large cross section is that inferences are robust to serial correlation across time. Therefore, we can obtain consistent coefficient estimates with panel data standard errors that are robust to heteroskedasticity and

[7] Wiersma (2007) uses the Crawford specification. Wiersema's study uses data for one firm for a three-year period and thus his data is more amenable to the Crawford specification.

[8] Given the large number of clinical lab tests conducted by the hospitals, asymptotically these two models are equivalent. Goldberg and Touw (2003, 32-33) show that the two specifications are equal in the continuous case and Lee (1997, 41-42) demonstrates the asymptotic equivalence of two specifications in the discrete case.

serial correlation of unknown forms by clustering the standard errors at the lab level (Wooldridge 2010a). The empirical form of the learning curve model is:

$$\text{Cost or hours per unit}_{it} = \beta_0 + \beta_1.\text{Cumulative units}_{it-1} + e_{it} \quad (1)$$

We extend equation (1) to control for economies of scale (Berndt 1991). We also extend the model to assess the effect of quality on learning rates. The interaction of *Low quality hospital* with $Cumulative\ Units$ and *LOS* with $Cumulative\ Units$ allows us to test H2. We interact *For-profit hospital* with $Cumulative\ Units$ to examine whether for-profit hospitals have a different learning rate compared to non-profit and government hospitals, which allows us to test H3. To test H4, we interact *High technical efficiency hospital* indicator with $Cumulative\ Units$ to examine whether hospitals with high efficiency experience higher learning rates. Finally, we include lab fixed effects (c_i).[9] The full model is:

$$\begin{aligned}\text{Cost per unit or hours per unit}_{it} = \\ \beta_0+\beta_1\text{Cumulative units}_{it}+\beta_2\text{Scale}_{it}+\beta_3\text{Cumulative units}_{it}\times\text{Low quality hospital}_i \\ +\beta_4\text{LOS}_{it}+\beta_5\text{Cumulative units}_{it}\times\text{LOS}_{it}+\beta_6\text{Cumulative units}_{it}\times\text{For-profit hospital}_i \\ +\beta_7\text{Cumulative units}_{it}\times\text{High technical efficiency hospital}_i+\beta_8\text{Lab employee intensity}_{it} \\ +\beta_9\text{Lab Importance}_{it}+\beta_{10}\text{Depreciation}_{it}+\beta_{11}\text{Outsourcing}_{it}+c_i+y_t+e_{it} \quad (2)\end{aligned}$$

In equation (2), β_1 is the percentage change in the average cost per unit for a percentage change in the cumulative units, which measures learning effects. H1 predicts that the average cumulative direct cost per unit reduces with an increase in cumulative clinical lab tests Accordingly, we expect $\beta_1 < 0$. The effect of economies of scale on the cumulative average hours (or cost) per clinical test is provided by β_2. H2 posits that low-quality hospitals have a higher learning rate than high-quality hospitals. Thus, we expect the coefficient on the interaction between cumulative units and low-quality hospital, β_3, to be less than zero, and the coefficient on

[9] In the regressions, all the continuous variables are demeaned in the interaction to control for multi-collinearity and to make the main effects interpretable as average partial effects (Wooldridge 2015).

the interaction between cumulative units and LOS (which indicates high quality), β_5 to be greater than zero. H3 posits that for-profit hospitals have a lower rate of learning than non-profit and government hospitals. Thus, we expect $\beta_6 > 0$. H4 predicts that high technical efficiency hospitals have a higher rate of learning; thus, we expect $\beta_7 < 0$.

Time-constant differences in hospitals (e.g., location) could be correlated with cumulative units. Therefore, equation (2) uses lab fixed effects (c_i).[10] We include year fixed effects (y_t) to control for technological changes that can shift the cost functions of the industry. We cluster standard errors by lab to ensure that the inferences are robust to serial correlation and heteroskedasticity.

4. Results

Table 2, Panel A reports the summary statistics for the period 1997-2015.[11] The mean technical hours per unit and supervision hours per unit are negative because these variables are measured on a logarithmic scale. On average, hospitals use less than ten minutes per unit of lab test. The mean for technical wages per unit and salary per unit indicate that the average cost per unit of lab test is less than $3.

Table 2, Panel B measures the variables used in Panel A on the actual scale. The mean technical hours per unit is 0.134 which translates to around 8 minutes and mean supervision hours per unit is 0.021 hours, which is equivalent to approximately 1.3 minutes. In our sample, the average direct cost per unit of clinical lab test is $6.53. The average lab performs over 550,000 clinical lab tests. The mean cumulative tests for a lab are around 4.5 million with a positive skewness due to the existence of large hospitals. The average length of stay is 6 days with a maximum stay of 37 days. The importance of the lab for an average hospital is approximately

[10] The main effects for low-quality hospital, for-profit hospital, and high technical efficiency hospital are not included because they will be perfectly correlated with lab fixed effects.
[11] All variables are winsorized at the 1% and 99% level.

14% measured as productive hours in a clinical lab for technical and specialist employees as a percentage of productive hours for all technical and special employees in the hospital. Table 3 contains correlations for the variables used in the analyses. Hours and wages are highly correlated in the case of both technical and supervisory labor, which implies that they measure the same underlying construct and are thus suitable for testing learning curve hypotheses.

– Insert Tables 2 and 3 here –

Table 4 reports the estimation results for equation 2 using technical hours per unit (column 1) and technical wages per unit (column 2) as the dependent variable. In both columns, the coefficient on *Cumulative units* is negative. Thus, as the percentage of cumulative units increases, technical hours per unit (column 1) and technical wages per unit (column 2) reduce. These results are consistent with H1 and suggest that technical labor in clinical labs exhibits significant learning curve effects. The interaction *Cumulative units* × *Low quality hospital* is negative indicating that hospitals with above median mortality rates have significantly better learning curves relative to hospitals with lower mortality rates. The interaction *Cumulative units* × *LOS* is positive indicating that as process quality increases, learning curves become worse. These results imply the presence of tradeoffs between cost and quality, as predicted by H2. Thus, low quality hospitals, that is hospitals that have higher mortality or lower LOS exhibit better learning curves. For-profit hospitals have worse learning curves as indicated by the positive interaction between *Cumulative units* × *For-profit hospital*, supporting H3. The interaction *Cumulative units* × *High technical efficiency hospital* is negative, which implies that hospitals with mean or greater technical efficiency scores have a higher rate of learning. This provides support for H4.

For robustness, we perform a regression-based test for the difference in estimates between our fixed effects model in Table 4 and an alternative random effects model. We include time

averages of variables that change over time, re-estimate equation 2 using random effects, and perform a joint significance test (Mundlak 1978). The time averages are jointly significant at the 1% level, indicating that time invariant hospital characteristics are correlated with the explanatory variables, warranting the fixed effects estimation.[12]

– Insert Table 4 here –

We perform a similar analysis with supervision hours per unit and supervision wages per unit as dependent variables. Table 5 reports the results for equation 2 for supervision hours per unit (Column 1) and supervision wages per unit (Column 2). The results show the following. First, the significant coefficient on *Cumulative units* indicates that learning curve effects are present in both supervision hours per unit (Column 1) and supervision wages per unit (Column 2), consistent with H1. Thus, clinical labs exhibit learning for supervisory labor. Second, neither of the quality variables influences learning curves as evidenced by the insignificant coefficients for the interaction of *Cumulative units* × *Low quality hospital* and *Cumulative units* × *LOS*. Thus, the cost-quality tradeoff does not adversely affect the learning rate for supervisors and managers, like it does for technical labor. Because technical labor is directly involved in providing the service (lab test), and reimbursements for lab tests are based on a fixed fee per test, the quality-cost tradeoff occurs only for technical labor. The interaction of *Cumulative units* × *For-profit hospital* is not significant, indicating that for-profit hospitals do not have less favorable learning rates for supervisory labor. Thus, H3 is not supported for supervisors and managers. For-profit hospitals typically spend more on administrative labor than nonprofit hospitals and are more likely to cut clinical staff before they cut administration (Woolhandler and Himmelstein 1997). The interaction of *Cumulative units* × *High technical efficiency hospital* is negative and

[12] There are two advantages of using a regression-based test rather than the Hausman test to compare fixed effects and random effects estimations (Guggenberger 2010). First, the Hausman test only compares the coefficients of time varying variables. Second, adding time averages allows a regression-based Wald test that is robust to violations of the random effects variance covariance matrix (Wooldridge 2010b).

significant. Thus, we find support for H4 with respect to supervisory labor. The overall level of technical efficiency favorably affects learning curves for supervisory labor.

– Insert Table 5 here –

We next estimate the effect of learning on salary per unit and direct cost per unit (Table 6). This analysis captures the overall cost of performing lab tests, after including laboratory-level overheads such as depreciation and administrative costs. The coefficient on *Cumulative units* indicates the presence of learning curves for both salary per unit (Table 6, column 1), and direct cost per unit (Table 6, Column 2), consistent with H1. The *Cumulative units* × *Low quality hospital* interaction is not significant. Thus, the cost-quality tradeoff is not present in salary and direct cost per unit. This result further highlights that cost-quality tradeoffs affect only technicians directly involved with lab testing. Thus, analysis that examines aggregate cost pools such as direct cost or total salary is likely to miss the effect of contextual factors such as cost-quality tradeoffs on learning curves. For better identification of learning curves, analysis of task-level data is essential. The interaction between *Cumulative units* × *For-profit hospital* is positive and significant for salary per unit indicating more adverse learning curves in for-profit hospitals. Similarly, the interaction between *Cumulative units* × *High technical efficiency hospital* is negative and marginally significant level for salary per unit indicating that hospitals with higher technical efficiency have better learning curves in their salary cost pools.

– Insert Table 6 here –

5. Supplemental Analysis

Product-mix scope and learning

In addition to technical efficiency, product-mix scope also influences learning curves. Clinical labs can choose to specialize on a few types of tests, or they can have a broad product scope and service a larger variety of tests. If tasks are informationally related, then knowledge about any one task is portable; that is, it can help in the operations of the other tasks (Mitchell 2000). The

decision to specialize versus adopt a broad task mix is an important dimension of lab design that can influence learning curves. On the one hand, specialization enables workers devote all their time and energy on one task, which can lead to performance gains (Fisher and Ittner 1999). On the other hand, learning on one task can increase absorptive capacity and enhance learning on other tasks (Schilling et al. 2003). Related task variability increases the salience of associations and provides a deeper understanding of the conceptual foundations of knowledge.

We examine the effect of product mix scope on learning. We operationalize product mix scope as *lab breadth*, which is an indicator variable that equals one if all types of laboratory testing services in the year t are available within the hospital and zero otherwise. The services are - anatomical pathology, chemistry, clinical pathology, cytogenetics, cytology, hematology, histocompatibility, immunology, microbiology, necropsy, serology, and surgical pathology. We interact this variable with cumulative units and estimate equation 2. We drop technical efficiency in this analysis, since scope can be considered a dimension of technical efficiency at the task level. The results are provided in Table 7. The interaction between *Cumulative units* × *Lab breadth* is negative and significant for both technical hours per unit (Table 7, column 1) and technical wages per unit ((Table 7, column 2) indicating that lab breadth increases learning rates. Thus, related task variability increases learning rates.

– Insert Table 7 here –

Robustness to pre-existing trend and scope for learning

We conduct additional analysis to rule out the possibility that the contextual factors that affect learning curves, namely cost- quality tradeoffs and organization ownership, arise from a pre-existing cost pattern that does not involve managerial choices. For example, if low-quality hospitals have a very high cost at the beginning of the sample period, then they have a scope for better learning curves over the sample period. Univariate analysis for 1997 (first year in our sample period) indicates that the difference in means for average technical wages per unit

(average technical hours) between low quality hospitals and high-quality hospitals is 0.12 (0.01) (t = 0.87 [0.85]). Thus, there was no significant difference in technical wages per unit (technical hours per unit) for the two groups of hospitals at the start of the sample period, indicating that the cost-quality tradeoff is intentional and arises from managerial choices during the period of our study. Figure 2a (2b) plots the average technical wages (technical hours) for hospitals separated by quality during our sample period. Low quality hospitals appear to be making a cost-quality tradeoff, as a result of which the higher learning rate in low-quality hospitals becomes pronounced from 2008. Similarly, we find no significant difference in technical wages per unit (technical hours per unit) for hospitals separated by ownership during the first year of the sample period. Univariate analysis for 1997 indicates that the difference in means for average technical wages per unit (average technical hours) between for-profit and other hospitals is 0.09 (0.01) (t = 0.51 [0.31]). Figure 2c (2d) indicates that for-profit hospitals have adverse learning curves for technical wages (technical hours), which becomes pronounced from 2005. Thus, our results are not driven by underlying differences in hospital types at the beginning of the sample period.

– Insert Figure 2 here –

Economic Significance of Learning Rates

Appendix C uses the estimation results from Table 4 column 2 and provides a numerical example of the difference in cost with and without the learning curve effects. The effects of learning on unit cost reduction are substantial and range from 11.36% (high-quality hospitals) to 13.30% (low-quality hospitals).[13] In the absence of learning curve effects, the total cost of 4 million lab tests is $6.68 million. Learning curves result in a $0.76 ($0.89) million reduction in cost for high quality hospitals (low quality hospitals).

[13] Higher (lower) learning curve ratios indicate slower (faster) rate of learning.

6. Conclusions

Literature in cost accounting has attempted to open the ‘‘black box’’ of cost behavior through theoretical and methodological innovations (Balakrishnan and Soderstrom 2000; Banker et al. 2018). These innovations have provided insights into firm-, industry-, and market-level influences that drive cost behavior, such as resource adjustment costs, managerial expectations, corporate governance, product strategy, demand uncertainty, regulation, and national culture. At the same time, more theory-driven research is required that opens the black box of cost behavior and uses context-specific data to obtain micro-level insights into the contextual and operational factors that influence costs.

We attempt to open the black box of cost behavior using task-level data and learning curve theory. Using clinical laboratory as an empirical setting, we provide evidence that employee learning introduces non-linearity in cost functions. We find evidence of substantial learning effects. For technical and specialist lab staff we find learning curve ratios in the range of 84-90% indicating that technical labor cost reduces by 10-16% when cumulative lab tests double. We find that a focus on quality diverts employees' attention from learning for cost reduction to quality improvements. Hospitals with higher quality (mortality rates below the median, or longer LOS) appear to make a cost-quality tradeoff whereby they improve quality, which adversely affect their learning rates for technical labor. Overall, we find results that are consistent with the theory of learning.

Our study has implications for future research regarding the effect of learning curve on medical as well as cost outcomes. Balakrishnan and Soderstrom (2000) examine congestion costs in maternity care and find that congestion costs are associated with increased C-Section rates for at-risk patients where physician discretion is a prominent factor. It would be interesting to examine if hospitals with higher learning curves have different operating processes and controls that influence the likelihood of false positive or false negative test results. Another extension is to

explore whether lab tests that are considered more strategic have different learning rates. Balakrishanan and Gruca (2008) find that costs are stickier in direct patient care departments than in support departments. In the context of lab tests, situations where errors can be catastrophic, such as blood enzyme tests for patients on the throes of a heart attack (hourly troponin T (TnT) and troponin I (TnI) levels) could have less favorable learning curves.

Our study provides evidence that learning curves are an important driver of non-linearities in cost functions. By choosing a specific, labor-oriented task, we provide evidence of learning curves in a granular manner. Our findings have practical implications and can be useful for modeling non-linearities in budgeting and control systems. We also contribute to the healthcare literature and show that employee learning can be a source of value in health care. An important component of value enhancement is to identify reliable sources of cost reduction that do not compromise patient quality. Porter and Lee (2016, 1047) mention "value improvement is not business as usual; it is an entirely new way of managing." Our results indicate that organizations would benefit from designing mechanisms that encourage employee retention to lock-in the benefits from employee learning. Finally, bending the healthcare cost curve is a national priority. Our results point toward another mechanism -namely employee learning- for achieving this goal.

Appendix A
Variable Definitions

The following variables are constructed using the Hospital Annual Financial Disclosure Report available with the Office of Statewide Health Planning and Development (OSHPD). The average Consumer Price Index (CPI) is computed from the monthly CPI data for all items in U.S. city average, all urban consumers, not seasonally adjusted obtained from the Bureau of Labor Statistics. All other variables are obtained from the Hospital Annual Financial Disclosure Report.

Variable	Definition
Dependent Variables	
Technical hours per unit	Natural logarithm of cumulative hours worked by lab technicians in a clinical lab up to and including year *t*, divided by the cumulative number of clinical tests conducted by the lab up to and including year *t*.
Technical wages per unit	Natural logarithm of the sum up to and including year *t* of the product of technical hours worked by lab technicians in a clinical lab and the deflated average hourly wage rate for lab technicians divided by the cumulative number of clinical tests conducted by the lab up to and including year *t*.
Supervision hours per unit	Natural logarithm of cumulative hours worked by managers and supervisors in a clinical lab up to and including year *t*, divided by the cumulative number of clinical tests conducted by the lab up to and including year *t*.
Supervision wages per unit	Natural logarithm of the sum up to and including year *t* of the product of supervision hours worked by lab supervisors in a clinical lab and the deflated average hourly wage rate for lab supervisors divided by the cumulative number of clinical tests conducted by that lab up to and including year *t*.
Salary per unit	Natural logarithm of deflated salaries and wages incurred by a clinical lab up to and including year *t* divided by the cumulative number of clinical tests conducted by that lab up to and including year *t*.
Direct cost per unit	Natural logarithm of cumulative deflated direct expenses of a clinical lab up to and including year *t* divided by the cumulative number of clinical tests conducted by that lab up to and including year *t*.
Independent Variables	
Cumulative units	Natural logarithm of cumulative clinical lab tests conducted up to and including year $\mathrm{t}-1$ for a clinical lab.
Scale	Natural logarithm of clinical tests conducted by a clinical lab in the current year (*t*).
Low quality hospital	An indicator variable equal to one if the average mortality rate for the hospital where the lab is situated is above the median of the average mortality rates for all hospitals during the entire sample period and zero otherwise.
LOS	Natural logarithm of total patient days divided by total discharges in the current year (t) for the hospital where the lab is situated.

For-profit hospital	An indicator variable equal to one if the hospital is owned by investors and zero otherwise.
High Technical efficiency hospital	An indicator variable equal to one if the technical efficiency score for the hospital as per Data Envelopment Analysis (DEA) falls on or above the mean score of the technical efficiency for the entire sample and zero otherwise. Technical efficiency scores are computed using linear programming with logarithm of net patient revenue as the output and logarithm of hospital full time equivalent (FTE), logarithm of operating expenses, and logarithm of total assets as inputs. All the variables are aggregated over the entire sample period to compute technical efficiency scores.
Lab Employee Intensity	Natural logarithm of productive hours worked by technical and specialist employees in the clinical lab divided by gross patient revenue generated by the clinical lab.
Lab Importance	Natural logarithm of productive hours worked by technical and specialist employees in the clinical lab divided by total productive hours worked by technical and specialist employees in the hospital where the lab is situated.
Depreciation	Natural logarithm of depreciation of assets employed in clinical labs.
Outsourcing	Purchased services as a percentage of total direct expenses.
Lab breadth	An indicator variable equal to one if all laboratory services are available within the hospital and zero otherwise. The services include - Anatomical Pathology, Chemistry, Clinical Pathology, Cytogenetics, Cytology, Hematology, Histocompatibility, Immunology, Microbiology, Necropsy, Serology, Surgical Pathology

Appendix B

Variable Location in Hospital Disclosure Report

This table provides the exact location in the Hospital Annual Financial Disclosure Report for the variables defined in Appendix A.

Variable	Page	Column	Line
Technical hours per unit			
Technical hours	21	4	260
Technical wages per unit			
Average hourly rate for technical staff	21	3	260
Supervision hours per unit			
Productive hours	21	2	260
Supervision cost per unit			
Average Cost Center Rate	21	1	260
Salary per unit			
Salaries and wages	17	1	260
Direct cost per unit			
Direct Expenses	17	10	260
Cumulative units *(sum of clinical tests for each lab up to and including year t)*	4	1	260
Scale			
Clinical tests in year t	4	1	260
LOS			
Total Patient days	4	4,5	150
Total Discharges	4	12	150
Patient days (long term care)	4	4,5	100, 101, 105, 110, 115, 120, 125
Discharges (long term care)	4	12	100, 101, 105, 110, 115, 120, 125
For-Profit hospital	1	2	20, 25, 30
Lab Employee Intensity			
Gross Patient Revenue of clinical lab	12	23	260
Lab Importance			
Technical hours for the hospital	21, 22	4	(150, 225, 405), (10, 50, 150, 200, 300, 350, 370)
Depreciation	17	7	260
Outsourcing			
Purchased Services	17	6	260
Lab breadth	2	1,2	(370, 375, 380, 385, 390, 395, 400, 405), (5,10,15,20)

Appendix C
Numerical Example of Learning Curve Effects

In this appendix, we provide an example based on the results for the average wages per unit (Table 4 column 2) to document the economic significance of cost reductions due to the learning curve effect.

1. Calculation of learning curve ratio and learning rate.

This table shows the learning curve ratio and reduction rate in technician wages for clinical laboratories in low-quality hospitals and high-quality hospitals. The learning index is the average partial effect of cumulative units for low-quality hospitals and high-quality hospitals from the regression tabulated in Table 4, column 2 holding all other variables constant. Year fixed effects controls for any technological shock that affects all the labs in the state. Column (iii) computes the learning curve ratio using the learning index in column (ii). Column (iv) provides the reduction rate in unit cost when the clinical lab tests are doubled.

Variable	Learning index	Learning curve ratio	Reduction rate in unit cost
(i)	(ii)	(iii) $= 2^{(ii)} \times 100$	(iv) $= (1 - (iii)) \times 100$
Clinical labs in low quality hospitals	−0.206***	86.70%	13.30%
Clinical labs in high quality hospitals	−0.174***	88.64%	11.36%

2. Calculation of cost per clinical lab test using the learning rate computed in above table.

This table provides the cost per clinical lab test when the cumulative lab tests are doubled from 2 million clinical lab tests to 4 million clinical lab tests[14] holding the effects of other variables constant. The technical wages per clinical lab test is assumed to be \$1.67[15] at a cumulative quantity of 2 million clinical lab tests, which is obtained from the exponential of the mean of cumulative lab tests on log scale. Column (ii) provides the cost per clinical lab test for low-quality hospitals and column (iii) provides the cost per clinical lab test for high-quality hospitals. Column (iv) provides the difference in cost due to learning among low quality and high-quality hospitals.

	Quality		
	Low-quality hospitals	High-quality hospitals	Difference in cost
(i)	(ii)	(iii)	(iv)
Clinical Labs	$(1 - 0.133) \times 1.67$ $=1.448$	$(1 - 0.1136) \times 1.67$ $= 1.480$	$(1.480 - 1.448) \times 4$ $= \$0.128\ million$

Therefore, doubling the units from 2 million lab tests to 4 million lab tests over an average period of three and a half years is expected to increase the technician wage cost for high-quality hospitals by \$ 0.128 million compared to low quality hospitals.

[14] The average number of yearly clinical lab tests in the sample is about 550,000, which implies that an average hospital can expect cost reductions described in the table below to occur over a period of three and a half years.
[15] \$1.671 is the mean of the predicted value of the average cost per clinical lab test obtained by averaging the predicted cost per unit for the cumulative units in the range of 1.95 million and 2 million. The mean of the actual average cost per unit is \$1.673. Similarly, the mean of the predicted value of the average cost per clinical lab test for the cumulative units in the quantity range of 4 million and 4.05 million is \$1.401 per clinical lab test whereas the mean of the actual average cost per unit is \$1.395 per clinical lab test.

3. Cost reduction from learning curve effect

This table shows the difference in cost for clinical labs with and without the learning curve effect. Column (iii) provides the total cost of 4 million lab test without the learning curve effect. Column (iv) provides the total cost of 4 million clinical lab test based on the learning curve ratios documented in column (ii). Column (v) computes the reduction in cost due to the learning curve effect.

Variable	Learning curve ratio	Total cost for 4 million clinical lab tests without learning curve effect ($Million)	Total cost of 4 million clinical lab tests with learning curve effect ($Million)	Cost reduction due to learning curve effect ($Million)
(i)	(ii)	(iii) $= 1.67 \times 4$	(iv)	(v) $=$ (iii) $-$ (iv)
Labs in low-quality hospitals	86.70%	6.68	$1.448 \times 4 = 5.79$	0.89
Labs in high-quality hospitals	88.64%	6.68	$1.480 \times 4 = 5.92$	0.76

References

ACLA (American Clinical Laboratory Association). 2017. *Economic Impact Study of Independent Clinical Laboratories*.

Adler, P. S., and K. B. Clark. 1991. Behind the Learning Curve: A Sketch of the Learning Process. *Management Science* 37 (3): 267–81.

Alexander, J. A., J. R. Bloom, and B. A. Nuchols. 1994. Nursing Turnover and Hospital Efficiency: An Organization-Level Analysis. *Industrial Relations: A Journal of Economy and Society* 33 (4): 505–20.

Amit, R. 1986. Cost leadership strategy and experience curves. *Strategic Management Journal* 7 (3): 281–92.

Anderson Jr, E. G., and K. Lewis. 2014. A dynamic model of individual and collective learning amid disruption. *Organization Science* 25 (2): 356–76.

Anderson, M. C., R. D. Banker, and S. N. Janakiraman. 2003. Are selling, general, and administrative costs 'sticky'? *Journal of Accounting Research* 41 (1): 47–63.

Andreasen, A. R., P. Kotler, and D. Parker. 2008. *Strategic marketing for nonprofit organizations*. Pearson/Prentice Hall Upper Saddle River, NJ.

Argote, L. 2013. *Organizational learning: Creating, retaining and transferring knowledge*. Springer Science & Business Media.

Argote, L., and D. Epple. 1990. Learning curves in manufacturing. *Science* 247 (4945): 920–24.

Arrow, K. J. 1962. The economic implications of learning by doing. *Review of Economic Studies* 29: 155–73.

Balakrishnan, R., L. Eldenburg, R. Krishnan, and N. Soderstrom. 2010. The influence of institutional constraints on outsourcing. *Journal of Accounting Research* 48 (4): 767–94.

Balakrishnan, R., and N. S. Soderstrom. 2000. The cost of system congestion: Evidence from the healthcare sector. *Journal of Management Accounting Research* 12 (1): 97–114.

Balakrishnan, R., and T. S. Gruca. 2008. Cost stickiness and core competency: A note. *Contemporary Accounting Research* 25 (4): 993–1006.

Banker, R. D., and D. Byzalov. 2014. Asymmetric cost behavior. *Journal of Management Accounting Research* 26 (2): 43–79.

Banker, R. D., D. Byzalov, S. Fang, and Y. Liang. 2018. Cost Management Research. *Journal of Management Accounting Research* 30 (3): 187–209.

Becchetti, L., S. Castriota, and S. Depedri. 2013. Working in the for-profit versus not-for-profit sector: what difference does it make? An inquiry on preferences of voluntary and involuntary movers. *Industrial and Corporate Change* 23 (4): 1087–120.

Becker, E. R., and F. A. Sloan. 1985. Hospital ownership and performance. *Economic Inquiry* 23 (1): 21–36.

Benkard, C. L. 2000. Learning and Forgetting: The Dynamics of Aircraft Production. *The American Economic Review* 90 (4): 1034–54.

Berndt, E. 1991. Costs, Learning Curves, and Scale Economies: From Simple to Multiple Regression. *The Practice of Econometrics: Classical and Contemporary*.

Boone, T., R. Ganeshan, and R. L. Hicks. 2008. Learning and knowledge depreciation in professional services. *Management Science* 54 (7): 1231–36.

Campbell, D., M. J. Epstein, and F. A. Martinez-Jerez. 2011. The Learning Effects of Monitoring. *The Accounting Review* 86 (6): 1909–34.

Carter, R. B., L. J. Massa, and M. L. Power. 1997. An examination of the efficiency of proprietary hospital versus non-proprietary hospital ownership structures. *Journal of Accounting and Public Policy* 16 (1): 63–87.

Cohen, W., and D. Levinthal. 1990. Absorptive Capacity: A New Perspective on Leaning and Innovation. *Administrative science quarterly* 35: 128–52.

Crawford, J. R. 1944. Learning curve, ship curve, ratios, related data. *Lockheed Aircraft Corporation* 144.
Crossman, E. R. F. W. 1959. A Theory of the acquisition of speed-skill. *Ergonomics* 2 (2): 153–66.
Cyert, R. M., and J. G. March. 1963. A behavioral theory of the firm. *Englewood Cliffs, NJ* 2: 169–87.
Datar, S. M., and M. V. Rajan. 2017. *Horngren's Cost Accounting*. Pearson.
Deily, M. E., and N. L. McKay 2006. Cost inefficiency and mortality rates in Florida hospitals. *Health Economics* 15: 419–31.
Debreu, G. 1951. The coefficient of resource utilization. *Econometrica: Journal of the Econometric Society* 19 (3): 272–92.
Ding, X. D. 2014. The effect of experience, ownership and focus on productive efficiency: A longitudinal study of U.S. hospitals. *Journal of Operations Management* 32 (1-2): 1–14.
Dutton, J. M., and A. Thomas. 1984. Treating progress functions as a managerial opportunity. *The Academy of Management Review* 9 (2): 235–47.
Epple, D., L. Argote, and R. Devadas. 1991. Organizational learning curves: A method for investigating intra-plant transfer of knowledge acquired through learning by doing. *Organization Science* 2 (1): 58-70.
Epple, D., L. Argote, and K. Murphy. 1996. An empirical investigation of the microstructure of knowledge acquisition and transfer through learning by doing. *Operations Research* 44 (1): 77–86.
Fama, E. F., and M. C. Jensen. 1983. Separation of Ownership and Control. *The Journal of Law & Economics* 26 (2): 301–25.
Fernald, D. H., W. D. Pace, D. M. Harris, D. R. West, D. S. Main, and J. M. Westfall. 2004. Event reporting to a primary care patient safety reporting system: a report from the ASIPS collaborative. *The Annals of Family Medicine* 2 (4): 327–32.
Fisher, M. L. and C. D. Ittner. 1999. The impact of product variety on automobile assembly operations: Empirical evidence and simulation analysis. *Management Science* 45 (6): 771–86.
Gaynor, M., H. Seider, and W. B. Vogt. 2005. The volume-outcome effect, scale economies, and learning-by-doing. *American Economic Review* 95 (2): 243–7.
Ghemawat, P., and A. M. Spence. 1985. Learning curve spillovers and market performance. *The Quarterly Journal of Economics* 100 (Supplement): 839–52.
Glock, C. H., E. H. Grosse, M. Y. Jaber, and T. L. Smunt. 2019. Applications of learning curves in production and operations management: A systematic literature review. *Computers & Industrial Engineering* 131: 422–41.
Goldberg, M. S., and A. Touw. 2003. *Statistical methods for learning curves and cost analysis*. CNA Corporation Alexandria United States.
Grieco, P.L. and McDevitt, R.C. 2017. Productivity and quality in health care: Evidence from the dialysis industry. *The Review of Economic Studies 84* (3): 1071-105.
Grosse, E. H., C. H. Glock, and S. Müller. 2015. Production economics and the learning curve: A meta-analysis. *International Journal of Production Economics* 170: 401–12.
Hansmann, H. 1980. The role of nonprofit enterprise. *The Yale Law Journal* 89 (5): 835–901.
Hirschmann, W. B. 1964. Profit from the learning-curve. *Harvard Business Review* 42 (1): 125–39.
Henderson, B. 1968. The experience curve. *BCG Perspectives* No. 87.
Holt, P. J. E., J. D. Poloniecki, D. Hofman, R. J. Hinchliffe, I. M. Loftus, and M. M. Thompson, 2010. Re-interventions, readmissions and discharge destination: modern metrics for the assessment of the quality of care. *European Journal of Vascular and Endovascular Surgery*. 39 (1): 49–54.

IOM (Institute of Medicine) 2001. *Crossing the Quality Chasm: A New Health System for the 21st Century*. Washington, D.C.: National Academy Press.
Ittner, C. D., and D. F. Larcker. 1997. Quality strategy, strategic control systems, and organizational performance. *Accounting, Organizations and Society* 22 (3-4): 293–314.
Guggenberger, P. 2010. The impact of a Hausman pretest on the size of a hypothesis test: The panel data case. *Journal of Econometrics* 156 (2): 337–43.
Jha, A. K., E. J. Orav, A. Dobson, R. A. Book, and A. M. Epstein 2009. Measuring efficiency: The association of hospital costs and quality of care. *Health Affairs* 28 (3): 897–906.
Joskow, P. L., and N. L. Rose. 1985. The effects of technological change, experience and environmental regulation on the construction costs of coal-burning generating units. *RAND Journal of Economics* 16 (1): 1–27.
Kelsey, S. F., S. M. Mullin, K. M. Detre, H. Mitchell, M. J. Cowley, A. R. Gruentzig, and K. M. Kent. 1984. Effect of investigator experience on percutaneous transluminal coronary angioplasty. *The American journal of cardiology* 53 (12): C56–64.
Kim, Y., R. Krishnan, and L. Argote. 2012. The Learning Curve of IT Knowledge Workers in a Computing Call Center. *Information Systems Research* 23 (3): 887–902.
Krugman, P. 1987. The narrow moving band, the Dutch disease, and the competitive consequences of Mrs. Thatcher: Notes on trade in the presence of dynamic scale economies. *Journal of Development Economics* 27 (1–2): 41–55.
Kumar, K., R. Subramanian, and C. Yauger. 1998. Examining the Market Orientation-Performance Relationship: A Context-Specific Study. *Journal of Management* 24 (2): 33.
Lee, D. A. 1997. *The cost analyst's companion*. Logistics Management Institute.
Lee, K.-H., S.-B. Yang, and M. Choi. 2009. The association between hospital ownership and technical efficiency in a managed care environment. *Journal of Medical Systems* 33 (4): 307–15.
Levin, L. Z. 2000. Organizational learning and the transfer of knowledge: An investigation of quality improvement. *Organization Science* 11 (6): 630–47.
Leibenstein, H. 1966. Allocative efficiency vs. X-efficiency. *The American Economic Review* 56 (3): 392–415
Lieberman, M. B. 1984. The learning curve and pricing in the chemical processing industries. *The RAND Journal of Economics* 15 (2): 213–228.
Lingsma H. F., A. Bottle, S. Middleton, J. Kievit, E. W. Steyerberg, and P. J. Marang- van de Mheen. 2018. Evaluation of hospital outcomes: The relation between length-of-stay, readmission, and mortality in a large international administrative database. *BMC Health Services Research* 18 (1): 116.
Lucas Jr, R. E. 1988. On the mechanics of economic development. *Journal of Monetary Economics* 22 (1): 3–42.
March, J. G., and H. A. Simon. 1958. Organizations. *New York. Wiley*.
McGlynn, E. A., P. G. Shekelle, S. Chen, D. P. Goldman, J. A. Romley, P. S. Hussey, H. De Vries, M. C. Wang, M. J. Timmer, J. Carter, and C. Tringale. 2008. Identifying, categorizing, and evaluating health care efficiency measures. *AHRQ Publication No. 08-0030. Agency for Healthcare Research and Quality, Rockville, MD*.
Mitchell, M. F. 2000. The scope and organization of production: Firm dynamics over the learning curve. *The RAND Journal of Economics* 31 (1): 180–205.
Mukamel, D. B., W. D. Spector, R. Limcangco, Y. Wang, Z. Feng, and V. Mor. 2009. The costs of turnover in nursing homes. *Medical care* 47 (10): 1039–45, https://doi.org/10.1097/MLR.0b013e3181a3cc62.
Mukhopadhyay, T., P. Singh, and S. H. Kim. 2011. Learning curves of agents with diverse skills in information technology-enabled physician referral systems. *Information Systems Research* 22 (3): 586–605.

Mundlak, Y. 1978. On the pooling of time series and cross section data. *Econometrica: Journal of the Econometric Society*: 69–85.
Newhouse, J., 1970. Toward a theory of non-profit institutions: An economic model of a hospital. *American Economic Review* 60 (1): 64–74.
Ngo, A., P. Gandhi, and W. G. Miller. 2017. Frequency that Laboratory Tests Influence Medical Decisions. *The Journal of Applied Laboratory Medicine: An AACC Publication* 1 (4): 410–4.
Nonaka, I., and H. Takeuchi. 1995. *The knowledge-creating company: How Japanese companies create the dynamics of innovation*. Oxford university press.
O'Brien-Pallas, L., P. Griffin, J. Shamian, J. Buchan, C. Duffield, F. Hughes, H. K. S. Laschinger, N. North, and P. W. Stone. 2006. The Impact of Nurse Turnover on Patient, Nurse, and System Outcomes: A Pilot Study and Focus for a Multicenter International Study. *Policy, Politics, & Nursing Practice* 7 (3): 169–79, https://doi.org/10.1177/1527154406291936.
Pisano, G. P., R. M. J. Bohmer, and A. C. Edmondson. 2001. Organizational Differences in Rates of Learning: Evidence from the Adoption of Minimally Invasive Cardiac Surgery. *Management Science* 47 (6): 752–68.
Porter, M. E., and E. O. Teisberg. 2006. *Redefining health care: creating value-based competition on results*. Harvard Business Press.
Porter, M. E., and T. H. Lee. 2016. From volume to value in health care: The work begins. *JAMA* 316 (10): 1047-8.
Shen, Y. C. 2003. Changes in hospital performance after ownership conversions. *INQUIRY: The Journal of Health Care Organization, Provision, and Financing* 40 (3): 217–34.
Schilling, M. A., P. Vidal, R. E. Ployhart, and A. Marangoni. 2003. Learning by doing something else: Variation, relatedness, and the learning curve. *Management Science* 49 (1): 39–56.
Sood, N., P. J. Huckfeldt, D. C. Grabowski, J. P. Newhouse, and J. J. Escarce 2013. The effect of prospective payment on admission and treatment policy: Evidence from inpatient rehabilitation facilities. *Journal of Health Economics* 32: 965–79.
Spence, A. M. 1981. The learning curve and competition. *The Bell Journal of Economics*: 49–70.
Stelfox, H. T., and S. E. Straus 2013. Measuring quality of care: Considering measurement frameworks and needs assessment to guide quality indicator development. *Journal of Clinical Epidemiology* 66 (12): 1320–7.
Steven, G. 2010. The learning curve. The key to future management? *Chartered Institute of Management Accountants (CIMA)* 6: 12.
Stukel, T. A., E. S. Fisher, D. A. Alter, A. Guttmann, D. T. Ko, K. Fung, W. P. Wodchis, N. N. Baxter, C. C. Earle, and D. S. Lee. 2012. Association of hospitals spending intensity with mortality and readmission rates in Ontario hospitals. *JAMA* 307 (10): 1037–45.
Rapping, L. 1965. Learning and World War II production functions. *The Review of Economics and Statistics*: 81–6.
Reeves, M., G. Stalk, and F. S. Pasini 2013. BCG classics revisited: The experience curve. https://www.bcg.com/publications/2013/growth-business-unit-strategy-experience-curve-bcg-classics-revisited.aspx Accessed: 2020-04-13.
Rerup, C., and M. S. Feldman. 2011. Routines as a source of change in organizational schemata: The role of trial-and-error learning. *Academy of Management Journal* 54 (3): 577–610.
Thompson, P. 2012. The relationship between unit cost and cumulative quantity and the evidence for organizational learning-by-doing. *Journal of Economic perspectives* 26 (3): 203–24.
Tiemann, O., J. Schreyögg, and R. Busse 2012. Hospital ownership and efficiency: A review of studies with particular focus on Germany. *Health Policy* 104 (2): 163–71.

Tompkins, C. P., S. H. Altman, and E. Eilat 2006. The precarious pricing system for hospital services. *Health Affairs* 25 (1): 45–56.
Travers, E., and C. Krochmal. 1988. A new way to determine test cost per instrument. Part I. *MLO: Medical Laboratory Observer* 20 (10): 24.
Valdmanis, V. G. 1990. Ownership and technical efficiency of hospitals. *Medical Care* 28 (6): 552–61.
West, D. R., W. D. Pace, L. M. Dickinson, D. M. Harris, D. S. Main, J. M. Westfall, D. H. Fernald, and E. W. Staton. 2009. Relationship between patient harm and reported medical errors in primary care: A report from the ASIPS Collaborative.
Wiersma, E. 2007. Conditions that shape the learning curve: Factors that increase the ability and opportunity to learn. *Management Science* 53 (12): 1903–15.
Wooldridge, J. M. 2010a. *Econometric analysis of cross section and panel data*. MIT press.
———. 2010b. Correlated random effects models with unbalanced panels. Michigan State University, Department of Economics.
———. 2015. *Introductory econometrics: A modern approach*. Nelson Education.
Woolhandler, S., and D. U. Himmelstein. 1997. Costs of care and administration at for-profit and other hospitals in the United States. *New England Journal of Medicine* 336 (11): 769–74.
Wright, T. P. 1936. Learning curve. *Journal of the Aeronautical Sciences* 3 (1): 122–128.
Yasaitis, L., E. S. Fisher, J. S. Skinner, and A. Chandra. 2009. Hospital quality and intensity of spending: is there an association? *Health Affairs* 28(Suppl1): w566–72.
Yelle, L. E. 1979. The learning curve: Historical review and comprehensive survey. *Decision sciences* 10 (2): 302–28.
Zollo, M., and S. G. Winter. 2002. Deliberate learning and the evolution of dynamic capabilities. Organization science 13 (3): 339–51.

Figure 1. The figure shows the difference between the effect of learning and economies of scale on cost per unit. Economies of scale involves a movement along the average cost curve whereas learning involves a shift in the average cost curve.

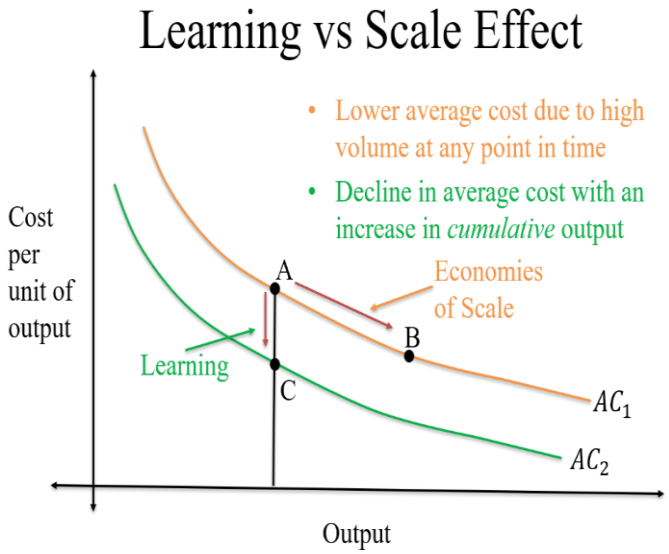

Figure 2. The figure shows the technical wages per unit and technical hours per unit for hospitals separated by quality and ownership. Fig 2a shows the mean of cumulative average technical wages per unit for hospitals separated by quality. Fig 2b shows the mean of cumulative average technical hours per unit for hospitals separated by quality. Fig 2c shows the mean of cumulative average technical wages per unit for hospitals separated by ownership. Fig 2d shows the mean of cumulative average technical hours per unit for hospitals separated by ownership.

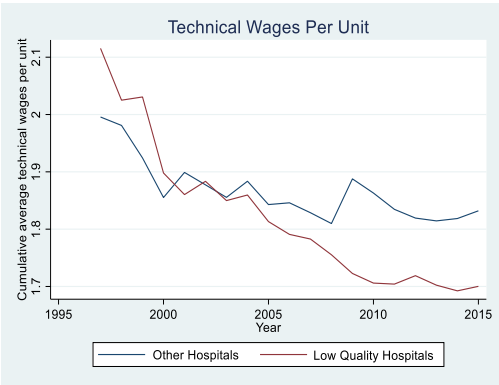

Fig 2a

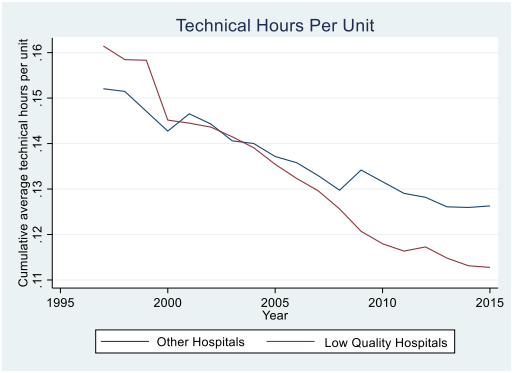

Fig 2b

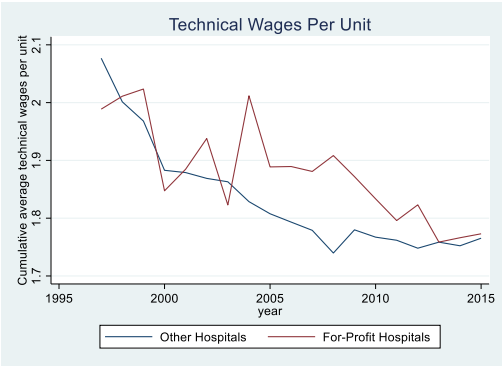

Fig 2c

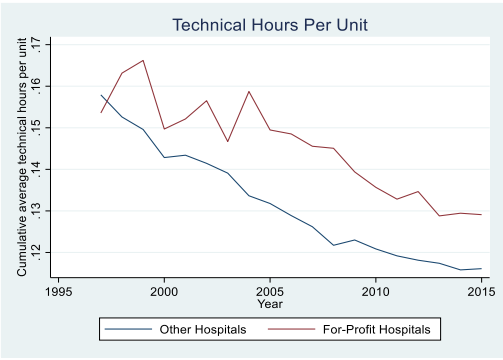

Fig 2d

TABLE 1
Sample composition by year

Year	Number of Hospitals in OSHPD database (1)	Number of Hospitals with clinical lab data (2)
1997	520	211
1998	484	228
1999	481	227
2000	449	212
2001	459	243
2002	427	245
2003	512	281
2004	465	225
2005	459	281
2006	456	287
2007	453	288
2008	453	286
2009	449	289
2010	450	290
2011	448	283
2012	446	294
2013	447	297
2014	450	291
2015	446	296
Total	**8,754**	**5,054**

Notes: This table presents the sample composition for the period 1997-2015 by year. Column 1 reports the number of hospitals in the OSHPD database. Column 2 presents the number of hospitals with non-missing data on the clinical lab variables during the sample period.

TABLE 2
Summary statistics

Panel A: Variables used in the analyses

Variables	N	Mean	Std dev	Q1	Median	Q3	Min	Max
Technical hours per unit	5,054	−2.114	0.457	−2.419	−2.101	−1.806	−3.231	−1.011
Technical wages per unit	5,054	0.520	0.421	0.238	0.524	0.810	−0.590	1.536
Supervision hours per unit	5,054	−4.166	0.742	−4.621	−4.202	−3.764	−5.965	−1.842
Supervision wages per unit	5,054	−1.208	0.709	−1.654	−1.250	−0.836	−2.823	1.065
Salary per unit	5,054	0.958	0.382	0.716	0.935	1.182	−0.107	2.005
Direct cost per unit	5,054	1.809	0.365	1.579	1.794	2.037	0.805	2.777
Cumulative units	5,054	14.486	1.439	13.617	14.619	15.519	10.300	17.534
Scale	5,054	12.668	1.138	11.979	12.766	13.447	9.213	15.148
Low quality hospital	5,054	0.499	0.500	0	0	1	0	1
LOS	5,054	1.553	0.481	1.323	1.474	1.634	0.760	3.607
For-profit hospital	5,054	0.248	0.432	0	0	0	0	1
High technical efficiency hospital	5,054	0.539	0.499	0	1	1	0	1
Lab Employee Intensity	5,054	−6.754	0.889	−7.363	−6.734	−6.110	−9.043	−4.718
Lab Importance	5,054	−2.068	0.509	−2.385	−2.041	−1.735	−3.545	−0.864
Depreciation	5,054	10.204	3.076	9.940	10.970	11.802	0	13.674
Outsourcing	5,054	14.113	9.455	8.702	12.382	17.126	0.386	71.723
Lab breadth	5,054	0.143	0.350	0	0	0	0	1

Panel B: Variables on actual scale

Variables	N	Mean	Std dev	Q1	Median	Q3	Min	Max
Technical hours per unit	5,054	0.134	0.063	0.089	0.122	0.164	0.040	0.364
Technical wages per unit	5,054	1.836	0.787	1.269	1.689	2.248	0.554	4.648
Supervision hours per unit	5,054	0.021	0.023	0.010	0.015	0.023	0.003	0.159
Supervision wages per unit	5,054	0.399	0.414	0.191	0.287	0.434	0.059	2.899
Salary per unit	5,054	2.810	1.162	2.047	2.548	3.261	0.899	7.426
Direct cost per unit	5,054	6.532	2.524	4.848	6.014	7.668	2.238	16.069
Cumulative units	5,054	4,536,363	6,619,986	819,897	2,233,127	5,491,282	29,725	41,200,000
Scale	5,054	556,496	661,068	159,438	350,045	691,824	10,022	3,791,475
LOS	5,054	5.668	5.654	3.754	4.368	5.123	2.138	36.843
Lab Employee Intensity	5,054	0.002	0.002	0.001	0.001	0.002	0.000	0.009
Lab Importance	5,054	0.143	0.074	0.092	0.130	0.176	0.029	0.422
Depreciation	5,054	108,731	148,886	20,737	58,112	133,473	0	868,257
CPI	5,054	202.872	24.939	179.88	207.342	224.939	160.5	237.017

Notes: Panel A of this table reports the summary statistics for the variables used in the analyses for the clinical lab tests during the period 1997-2015 and panel B reports the summary statistics on actual scale (before taking logarithm) only for the variables that are used in the analyses on the logarithmic scale during the period 1997-2015. The variables in both panels are winsorized at 1% and 99. All the variables are as defined in Appendix A except that the computations in panel B are shown before taking the natural log.

TABLE 3
Correlations

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)
(1) *Technical hours per unit*	1																
(2) *Technical wages per unit*	0.930***	1															
(3) *Supervision hours per unit*	0.385***	0.369***	1														
(4) *Supervision wages per unit*	0.400***	0.420***	0.984***	1													
(5) *Salary per unit*	0.735***	0.850***	0.574***	0.624***	1												
(6) *Direct cost per unit*	0.655***	0.761***	0.551***	0.599***	0.914***	1											
(7) *Cumulative Units*	−0.401***	−0.341***	−0.520***	−0.486***	−0.430***	−0.423***	1										
(8) *Scale*	−0.390***	−0.359***	−0.574***	−0.559***	−0.461***	−0.434***	0.822 ***	1									
(9) *Low quality hospital*	−0.055***	−0.040**	0.006	0.006	−0.005	−0.027	−0.088***	−0.105***	1								
(10) *LOS*	−0.044**	−0.064***	0.064***	0.070***	−0.112***	−0.141***	−0.015	0.001	0.178 ***	1							
(11) *For-profit hospital*	0.095***	0.033*	0.149***	0.135***	−0.037**	−0.092***	−0.202***	−0.232***	−0.031	0.279 ***	1						
(12) *High technical efficiency hospital*	−0.156***	−0.144***	−0.137***	−0.122***	−0.115***	−0.107***	0.365 ***	0.488 ***	−0.112***	0.012	−0.027	1					
(13) *Lab Employee Intensity*	0.496***	0.377***	0.231***	0.180***	0.266***	0.225***	−0.485***	−0.316***	−0.058***	0.029 *	−0.082***	0.247 ***	1				
(14) *Lab Importance*	0.406***	0.325***	0.066***	0.049***	0.121***	0.066***	−0.230***	−0.208***	0.032 *	−0.155***	0.094 ***	0.230 ***	0.516 ***	1			
(15) *Depreciation*	−0.064***	−0.035*	−0.179***	−0.173***	−0.038**	0.018	0.284 ***	0.387 ***	−0.036*	−0.156***	−0.227***	−0.176***	−0.036*	−0.069 ***	1		
(16) *Outsourcing*	−0.121***	−0.134***	0.009	0.012	−0.158***	0.051***	−0.032*	0.004	−0.074***	0.177 ***	0.006	−0.006	−0.062***	−0.147 ***	−0.017	1	
(17) *Lab breadth*	−0.071***	−0.049***	−0.068***	−0.050***	−0.053***	−0.030*	0.261 ***	0.289 ***	−0.045**	0.031 *	−0.074***	−0.216***	−0.092***	−0.082 ***	0.102 ***	0.056***	1

Notes: This table reports correlations among the variables used in the analysis. All the variables are defined in Appendix A. Figures *, **, *** indicate significance at the two−tailed 10%, 5%, and 1% levels, respectively.

TABLE 4
Learning curve effects for technical labor

Variables		(1) Technical hours per unit	(2) Technical wages per unit
Cumulative units	H1 (−)	−0.178***	−0.174***
		(0.031)	(0.028)
Scale	(−)	−0.132***	−0.123***
		(0.016)	(0.015)
Cumulative units × *Low quality hospital*	H2 (−)	−0.042***	−0.032***
		(0.013)	(0.012)
LOS		0.029	-0.028
		(0.028)	(0.029)
Cumulative units × *LOS*	H2 (+)	0.045***	0.024*
		(0.013)	(0.013)
Cumulative units × *For-profit hospital*	H3 (+)	0.032**	0.025*
		(0.015)	(0.015)
Cumulative units × *High technical efficiency hospital*	H4 (−)	−0.026**	−0.022*
		(0.013)	(0.012)
Lab employee intensity		0.076***	0.057***
		(0.015)	(0.014)
Lab importance		0.056***	0.047**
		(0.021)	(0.018)
Depreciation		0.004***	0.005***
		(0.001)	(0.001)
Outsourcing		−0.002***	−0.002***
		(0.001)	(0.001)
Observations		5,054	5,054
Lab Fixed Effects		Yes	Yes
Year Fixed Effects		Yes	Yes
SE clustered by		Clinical Lab	Clinical Lab
Within R-squared		0.390	0.372
Time averages jointly significant		Yes	Yes

Notes: This table reports estimation results using fixed effects regressions for average cumulative technical hours per unit and average cumulative technical wages per unit of clinical lab test for the period 1997-2015. In column 1, the dependent variable is the natural logarithm of the average cumulative technical hours per unit of clinical lab test. In column 2, the dependent variable is the natural logarithm of the average cumulative technical wages per unit of clinical lab test. Technical wages for each year is deflated using an average Consumer Price Index (CPI) for that year. The constant is not reported because it does not have an economic interpretation. We separately include the time averages to test for random effects vs fixed effects estimator. The null for the joint significance test of the time averages is that the coefficient is not significantly different from zero. Standard errors are clustered by clinical lab and reported in parenthesis. All variables are defined in Appendix A. Figures *, **, *** indicate significance at the two-tailed 10%, 5%, and 1% levels, respectively.

TABLE 5
Learning curve effects for managerial labor

		(1)	(2)
Variables		Supervision hours per unit	Supervision wages per unit
Cumulative units	H1 (−)	−0.239***	−0.217***
		(0.041)	(0.042)
Scale	(−)	−0.185***	−0.186***
		(0.023)	(0.022)
Cumulative units × *Low quality hospital*	H2	0.009	-0.007
		(0.023)	(0.023)
LOS		−0.018	−0.024
		(0.049)	(0.049)
Cumulative units × *LOS*	H2	−0.010	−0.019
		(0.018)	(0.018)
Cumulative units × *For-profit hospital*	H3 (+)	0.018	0.020
		(0.025)	(0.024)
Cumulative units × *High technical efficiency hospital*	H4 (−)	−0.072***	−0.071***
		(0.023)	(0.022)
Lab employee intensity		−0.032	−0.038
		(0.025)	(0.025)
Lab importance		0.010	0.018
		(0.030)	(0.032)
Depreciation		0.004*	0.004
		(0.002)	(0.002)
Outsourcing		−0.003**	−0.002**
		(0.001)	(0.001)
Observations		5,054	5,054
Lab Fixed Effects		Yes	Yes
Year Fixed Effects		Yes	Yes
SE clustered by		Clinical Lab	Clinical Lab
Within R-squared		0.203	0.201
Time averages jointly significant		Yes	Yes

Notes: This table reports estimation results using fixed-effects regressions on average cumulative supervision hours per unit and average cumulative supervision wages per unit of clinical lab test for the period 1997-2015. In column 1, the dependent variable is the natural logarithm of the average cumulative supervision hours per unit of clinical lab test. In column 2, the dependent variable is the natural logarithm of the average cumulative supervision wages per unit of clinical lab test. Supervision wages for any year is deflated using an average Consumer Price Index (CPI) for that year. The constant is not reported because it does not have an economic interpretation. We separately include the time averages to test for fixed effects vs random effects estimator. The null for the joint significance test of the time averages is that the coefficient is not significantly different from zero. Standard errors are clustered by clinical lab and reported in parenthesis. All variables are defined in Appendix A. Figures *, **, *** indicate significance at the two-tailed 10%, 5%, and 1% levels, respectively

TABLE 6
Learning curve effects for aggregate cost pools

Variables		(1) Salary per unit	(2) Direct cost per unit
Cumulative units	H1 (−)	−0.185***	−0.197***
		(0.024)	(0.022)
Scale	(−)	−0.144***	−0.145***
		(0.013)	(0.012)
Cumulative units × *Low quality hospital*	H2	−0.012	−0.012
		(0.011)	(0.010)
LOS		−0.035	−0.028
		(0.025)	(0.031)
Cumulative units × *LOS*	H2	−0.001	0.004
		(0.010)	(0.011)
Cumulative units × *For-profit hospital*	H3 (+)	0.027**	0.003
		(0.011)	(0.011)
Cumulative units × *High technical efficiency hospital*	H4 (−)	−0.019*	−0.013
		(0.011)	(0.010)
Lab employee intensity		0.008	−0.010
		(0.012)	(0.011)
Lab importance		0.006	0.017
		(0.017)	(0.013)
Depreciation		0.005***	0.005***
		(0.001)	(0.001)
Outsourcing		−0.002***	0.001*
		(0.001)	(0.001)
Observations		5,054	5,054
Lab Fixed Effects		Yes	Yes
Year Fixed Effects		Yes	Yes
SE clustered by		Clinical Lab	Clinical Lab
Within R-squared		0.397	0.421
Time averages jointly significant		Yes	Yes

Notes: This table reports estimation results using fixed effects on average cumulative salary per unit or average cumulative direct cost per unit of clinical lab test for the period 1997-2015. In column 1, the dependent variable is the natural logarithm of the average cumulative salary per unit of clinical lab test. Salaries are deflated using an average Consumer Price Index (CPI) of that year before computing the sum. In column 2, the dependent variable is the natural logarithm of the average cumulative direct cost per unit of clinical lab test. The direct cost for any year is deflated using an average Consumer Price Index (CPI) of that year. The constant is not reported because it does not have an economic interpretation. We separately include time averages to test for random effects vs. fixed effects estimator. The null for the joint significance test of the time averages is that the coefficient is not significantly different from zero. Standard errors are clustered by clinical lab and reported in parenthesis. All variables are defined in Appendix A. Figures *, **, *** indicate significance at the two-tailed 10%, 5%, and 1% levels, respectively.

TABLE 7
Learning curve effects and product-mix scope

Variables		(1) Technical hours per unit	(2) Technical wages per unit
Cumulative units	H1 (−)	−0.192***	−0.185***
		(0.031)	(0.028)
Scale	(−)	−0.137***	−0.127***
		(0.016)	(0.015)
Cumulative units × *Low quality hospital*	H2 (−)	−0.039***	−0.029**
		(0.013)	(0.012)
LOS		0.035	−0.022
		(0.028)	(0.029)
Cumulative units × *LOS*	H2 (+)	0.045***	0.024*
		(0.013)	(0.013)
Cumulative units × *For-profit hospital*	H3 (+)	0.033**	0.026*
		(0.015)	(0.015)
Lab breadth		0.030	0.030
		(0.022)	(0.022)
Cumulative units × *Lab breadth*	H4 (−)	−0.025**	−0.025**
		(0.012)	(0.012)
Lab employee intensity		0.081***	0.061***
		(0.015)	(0.014)
Lab importance		0.050**	0.041**
		(0.021)	(0.018)
Depreciation		0.004***	0.005***
		(0.001)	(0.001)
Outsourcing		−0.002***	−0.002***
		(0.001)	(0.001)
Observations		5,054	5,054
Lab Fixed Effects		Yes	Yes
Year Fixed Effects		Yes	Yes
SE clustered by		Clinical Lab	Clinical Lab
Within R-squared		0.388	0.371
Time averages jointly significant		Yes	Yes

Notes: This table reports the estimation results using fixed effects regressions for the average cumulative technical hours per unit and average cumulative technical wages per unit of clinical lab test for the period 1997-2015. In column 1, the dependent variable is the natural logarithm of the average cumulative technical hours per unit of clinical lab test. In column 2, the dependent variable is the natural logarithm of the average cumulative technical wages per unit of clinical lab test. Technical wages for each year is deflated using an average Consumer Price Index (CPI) of that year. Lab breadth is defined as 1 if all the twelve laboratory services are available at the hospital and 0 otherwise. The constant is not reported because it does not have an economic interpretation. We separately include the time averages to test for random effects vs fixed effects estimator. The null for the joint significance test of the time averages is that the coefficient is not significantly different from zero. Standard errors are clustered by clinical lab and reported in parenthesis. All variables are defined in Appendix A. Figures *, **, *** indicate significance at the two-tailed 10%, 5%, and 1% levels, respectively.