“Insider Econometrics” and the Determinants of Productivity

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I. Introduction

> "Great advances have been made in theory and in econometric techniques, but these will be wasted unless they are applied to the right data." (Griliches, 1994, 2)

Griliches' 1994 presidential address considers the limited success economists had in trying to account for the productivity slowdown of the 1970's and 1980's, and "urges us toward the task of observation and measurement." While the 1990's forced economists to account for high rates of productivity growth instead of a productivity slowdown, empirical researchers were again confronted with the challenge of modeling and estimating organization-level determinants of productivity as analysts pointed to businesses' use of new computer-based information technologies (IT) possibly in conjunction with new methods of work organization and more skilled workforces (Bresnahan, Brynjolfsson, and Hitt, 2002) as likely causes for productivity growth during this period. In this paper, we summarize three methods for assembling data for an "insider econometrics" study of the productivity of organizations. We illustrate the method that we refer to as "informed survey analysis" using personally collected data from the U.S. valve-making industry, and we present estimates of the productivity effects of new IT-based technologies and worker training for establishments in this industry.

II. Three Methods for Conducting Insider Studies of Organizational Productivity

Griliches and Mairesse (1995, 22-4) describe why it is so challenging to assemble the "right data" to investigate productivity determinants of real organizations:

> "At the micro level, the firms or plants that we analyze differ a great deal, even within what one might think of as a well-defined 'industry' … They differ in the particular assortment of products they may produce … [and] in the inputs and technologies that they use to produce them … Unfortunately, standard census type data do not provide enough additional information or relevant product and

> plant characteristics to allow one to pursue a substantive analysis…To make further progress, we need to infuse [production functions] with new data and appropriate theoretical and econometric models for dealing with the real heterogeneity that is the hallmark of the world we live in." (Griliches and Mairesse, 1995, 22-4)

Ichniowski and Shaw (2003) use the term "insider econometrics" to describe productivity studies that combine extensive field work to assemble useful organization-level data sets with rigorous econometric hypothesis testing of the effects of organization-specific determinants of productivity. This section summarizes three approaches to "insider econometrics" studies.

Cross-Organization Studies Based on Plant Visits

Insider econometrics is defined by two broad principles. First, it uses field work to generate a detailed understanding of a specific production process, its technology and the nature of the work in a particular industry. This field work in turn provides valuable insights about how to model production in that industry and what data to collect to estimate those models. Second, detailed operating data from the industry are used to estimate econometric productivity models that permit convincing tests of hypotheses about the determinants of productivity.

One method of implementing insider econometrics is to gather data from firms on the very performance measures that they use in monitoring production. Ichniowski, Shaw, and co-authors implement this approach in their studies of the effects of human resource management practices on productivity in the steel industry, visiting about 85 plants in the steel industry to conduct interviews and obtain data.[1] This approach is, unfortunately, very costly and time-consuming.

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[1] Specifically, we visited 45 production lines of 20 companies in the U.S. integrated steel industry (Ichniowski, Shaw and Prennushi, 1997), 5 integrated steel mills at two Japanese companies (Ichniowski

Single Firm Studies

A second and more common way to conduct insider productivity research is to focus on the operations of a single firm. Insider insights about key production processes in the firm identify situations where individual employees, teams of workers, or separate establishments inside the same company comprise the production units. These within-firm studies then provide convincing analysis of the effects of changing personnel practices across these units. Examples include: Lazear's study (2000) of piece rates in windshield installation; Hamilton, Nickerson and Owan's study (2003) of team methods in apparel manufacturing; Gaynor, Rebitzer, and Taylor's study (forthcoming) of incentives in an HMO; Batt's study (1999) of teams in a telecommunications company; and studies by Bartel (2004) and by Bartel, Freeman, Ichniowski and Kleiner (2003) of employee satisfaction in bank branches of one Canadian company and one U.S. company, respectively. Of course, single firm studies cannot examine organization-specific characteristics that do not vary within the company, and cannot model the causes of the adoption of practices.

Insider Productivity Research with "Informed Surveys"

A third approach for collecting "the right data" for organization-level productivity studies is to obtain data from "informed surveys." Plant visits and interviews are conducted at a small sample of plants in an industry and then used to understand the industry's production process and technology and develop a narrow industry-specific survey. We illustrate this approach using our results from the valve industry below.

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and Shaw, 1999), and 34 production lines operated by 19 U.S. minimill companies (Boning, Ichniowski, and Shaw, 2001). Other insider studies noteworthy for visits and data from many companies and work sites include MacDuffie's (1995) analysis of productivity effects of HRM practices in automobile assembly plants and Clark's (1984) study of unions and productivity in the cement industry.

Note however, that others have utilized “informed surveys” that Census researchers with expertise in specific industries have tailored to specific industries or occupations.[2]

III. Insider Insights into the U.S. Valve Making Industry

To pursue this third approach for plants in the U.S. valve making industry (SICs 3491, 3492, 3494 and 3593), we conducted site visits and interviews to five valve-making plants in 1999-2000 and in 2002 (during survey development). A valve is typically a metal device attached to pipes that regulate the flow of liquids or gases – such as the flow of natural gas in a heating system, or the control of liquids in a chemical factory. The central production process in valve making is the machining phase. A simple valve would be made by taking a steel block or pipe and completing several processes on one or more machines; such as, etching grooves at each end for screwing the valve to pipes; boring holes at different spots to attach control devices, and then making and attaching the various devices that control the flow. Based on our visits and interviews at these sites, we developed an industry-specific survey to measure productivity, technologies, and work practices.[3]

Measuring Efficiency in the Machining Process

Machining itself involves *setup time* to program machines so they will perform the right combination of tasks for the valve’s specification, the actual *run time* to complete the machining, and *inspection time* to verify the quality of the valves. We measure these three components by asking survey respondents to provide setup time,

[2] Examples of the use of Census surveys are: Hubbard (forthcoming) and Baker and Hubbard (2003) for studies of the effects of information technologies in trucking; Garicano and Hubbard (2003) for their study of lawyers; and Syverson (2003) for his study of the cement industry. Kelley (1994, 2000) conducts her own survey of machine operations in 21 industries to study the effects of work organization and IT.

[3] The telephone survey was conducted in 2002-3 by The Office for Survey Research at the Institute for Public Policy and Social Research at Michigan State University. The response rate was 43 percent.

runtime, and inspection time in 1997 and 2002 for the product they produced the most over those years. Our survey results show that the production times for these products declined over the last five years (Table 1).

Technologies and Valve-Making Efficiency

Today, the central piece of equipment in the valve making production process is a CNC (Computer Numerically Controlled) machine that automates the machining process. While CNC machines have been in use for about thirty years, the capabilities of individual CNC machines improved dramatically in the 1990's as computer power increased. During our plant visits, managers described the primary way in which new CNC raise productivity – the increasing sophistication of the CNC machines results directly in a decrease in the number of machines needed to produce a given product. Therefore, we use NUMBER OF MACHINES used in a run of the plant's main product as our key measure of improvements in CNC technology.

Managers also identified two other technologies as important sources of improved operational efficiency: flexible manufacturing systems (FMS) that coordinate the runs across multiple machines through the use of sophisticated software; and new automated valve inspection equipment that uses laser probe technology to measure dimensions of valves precisely (AUTO SENSORS). In our survey, we asked if plants have these technologies, and when they were introduced. As shown in Table 1, these new technologies became increasingly common over time.

Skills, Training, and HRM Practices

These new technologies may be related to an increased demand for more skilled workers. We collect data in our valve industry survey to measure whether plants tried to increase worker skills through a training program in basic math and reading skills (BASIC TRAINING) or through training in new technical skills for operating new technologies (TECHNICAL TRAINING). Other survey questions ask about the use of HRM practices besides training programs, such as problem solving teams (TEAMS). All of these practices increase over time (Table 1).

IV. Conventional Productivity Estimates Using LRD Plant-Level Data

As a contrast with our own survey results for production, we first introduce standard production function results using the Census of Manufacturers Longitudinal Research Database (LRD) data for plants in the valve industry that responded to our own survey. We estimate a standard production function framework in which log of output (value of shipments minus change in inventories) is a function of logs of labor hours, capital (gross value of depreciable assets), and materials.

The results show that labor and materials inputs are always significant in these OLS regressions, and capital is never significant (Table 2). Before interpreting these preliminary results as evidence that capital in valve-making plants is relatively unproductive, a number of alternative possible interpretations could be explored. One could argue that valve making has fixed factor production characteristics and that variation in the labor input is the constraining factor in production (e.g., if some equipment lies idle due to lack of orders or labor shortages). One should also consider models that instrument the capital variable because it is measured with error or because it is endogenous. However, the simple estimates presented here will highlight the difference between standard data applications and the use of our survey data below, suggesting perhaps that "… measurement difficulties [that] may in fact be a major source of the failure … to explain what has happened to the economy." (Griliches, 1994, 10)

V. Estimates of the Determinants of Productivity Using an Informed Survey

Using our survey data, we regress measures of production time on our technology measures described above. The results are straightforward: the adoption of new technologies reduces production time in the stage of production where the technology is of value (columns 1, 3, 5 of Table 3). Using fewer machines to produce a product reduces setup times. Run time declines significantly in plants that adopt FMS technology. Inspection time declines with the introduction of new automated inspection equipment (AUTO SENSOR). *New IT-based production machinery improves the efficiency of the stage of production in which it is involved. New computer technologies do not improve the efficiency of phases of machining in which they are not involved.* These results stand in sharp contrast to results obtained with plant-level LRD data using similar OLS estimation methods that find that the partial correlation of capital and output is insignificantly different from zero. Moreover, the estimated efficiency gains due to new technologies in the survey data are sizable.

The effects of human resource management variables are more mixed. Skills training related to new technologies (TECH TRAINING) improves efficiency in setup times and run times. The introduction of teams and basic skills training are found to be uncorrelated with improvements in any of the machining time components. These results concerning the effects of improved worker skills reveal that initiatives designed to improve the specific skills needed to operate new technologies in the plant are in fact the initiatives that improve operational efficiency.

VI. New Data and Appropriate Models

When the researcher's goal is to uncover the effects of organizational practices or the effects of specific computer technologies on productivity, he should seek data that can be used to estimate more specific productivity models in which the variables of interest can be expected to have direct effects that can be interpreted in a meaningful way. As the Griliches and Mairesse (1995) passage above warns, standard census data are not rich enough to permit a substantive analysis of these issues. The problems that result from limitations of these data are well described in the literature – measurement error in the dependent variable (which includes changes in product mix and requires appropriate deflators to translate nominal values into quantities) and endogeneity and selection bias.[4] We show that models that express production time efficiency as a function of specific technologies appear to identify important effects of information technologies and training.

However, the question remains, given these new survey data, what theoretical and econometric models are now required? While this question is central to our on-going insider productivity research in the valve industry, we note here that, in addition to reducing the measurement error in the measures of productivity and inputs, our survey data also reduces the likelihood of endogeneity bias. Consider the SETUP_TIME regression. The only way that setup time can be reduced over time for the same product is if the technology has changed, either because workers are better able to use the existing technology (perhaps due to better training) or because there is new technology. Based on plant visits and our understanding of the production function, there is no reason for a

[4] For discussion of these issues, see Griliches and Mairesse (1995), Olley and Pakes (1996), Syversen (2003), and Levinsohn and Petrin (2003).

decline in setup time to *cause* a decline in the number of machines in use. Thus, some endogeneity problems are avoided with these data.

Two potential problems remain. First, there may be some omitted variable bias in our results, if, for example, a reduction in the number of machines used to produce a given product is correlated with unobserved contemporaneous changes in the organization. Here, the narrow scope of the productivity model (spanning the operations of only a few machines) limits this problem, and direct contact with the plants and their managers allow the researcher to investigate whether such confounding factors exist.

Second, there may be selectivity bias. It is likely that the adopters of new technologies (like new CNC machines that reduce the number of machines per product produced) are the plants that have the greatest to gain from the new technologies. Non-adopters are either dropping out of our sample if they go out of business, or may not earn the same returns to technological change as the adopters do. The key question regarding this plausible type of selectivity bias is – what is the goal of the study? If it is to estimate an unbiased return to the random adoption of new technologies (or the "average treatment effect"), that is a difficult task with any data including our informed survey data. If the goal is to understand the gains for those who are likely adopters (or the "treatment of the treated"), then the next step is to develop a model that simultaneously predicts the adoption of new technologies and their likely gains. The very advantage of moving beyond data of one firm to that of many firms utilizing comparable production processes is that longitudinal data that spans many organizations allow us to model jointly the gains to organizational change and the reasons why some adopt these processes while others do not (Boning, Ichniowski, and Shaw, 2003).[5]

VII. Conclusion

Insider econometric studies have typically used one of three alternative types of appropriate data for estimating organization-level production functions: data obtained from one firm to model production differences across individuals or units of production (like teams or branches) within that firm; production data obtained directly from visits to many companies' plants all employing a common production process; and finally, data from "informed surveys" that are tailored to elicit information about one specific production process. Using this "informed survey" approach, we show that there appears to be gains from the use of information technologies and personnel practices in the valve industry, gains that could not possibly be revealed using standard Census of Manufacturing data. Moreover, field visits enabled us to understand the production processes, output measures, and technologies in this industrial setting before econometric models of organization-level determinants of productivity are estimated. Not only does getting "the right data" matter a great deal, but so too does getting insiders' insights about what the right data really are.

[5] Another concern is that, by focusing on the production efficiency of producing one product, we miss changes in product mix that may well contribute to the returns to the adoption of new technologies.

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Table 1
Summary Statistics on Production Times in Valve Machining,
New Computer-Based Production Technologies, and HRM Practices

Panel A	***Mean Value for 1997***[1]	***Mean Value for 2002***[2]	***Log change between 1997 and 2002***
Setup time	0.49	0.28	-0.681
Run time	0.45	0.39	-0.371
Inspection time	0.05	0.03	-0.334
Total time	1.03	0.72	-0.481
Number of machines	5.63	4.97	-0.189

Panel B	***Fraction of obs. using equipment or HRM practices in 2002***	***Fraction of obs. adopting equipment or HRM practices bet. 1997 and 2002***
FMS	0.337	0.151
Auto sensors	0.283	0.137
3d Cad	0.738	0.387
Basic training	0.333	0.119
Technical training	0.726	0.211
Teams	0.647	0.298

1. In fractions of a day except for Number of machines.
2. In fractions of a day except for Number of machines.

Table 2
LRD Productivity Regressions
(Sample: Plants in Authors' Survey)

	(1)	(2)
	1997 Levels	1992-1997 First Differences
Log (Total Hours)	0.384*** (0.040)	0.219*** (0.041)
Log (Capital)	-0.010 (0.024)	-0.015 (0.026)
Log (Materials)	0.610*** (0.035)	0.516*** (0.036)
Observations	178	145
R-squared	0.938	0.721

Standard errors in parentheses
* significant at 10%; ** significant at 5%; *** significant at 1%

Table 3
1997 – 2002 First Difference Productivity Regressions Using Survey Data[a]

	(1)	(2)	(3)
Dependent Variable	Setuptime	Runtime	Inspect Time
Chg Number Machines	0.673*** (0.226)	0.225 (0.199)	0.125 (0.237)
New FMS	0.141 (0.270)	-0.416* (0.243)	0.330 (0.287)
New Auto Sensor	-0.093 (0.297)	0.486* (0.260)	-0.635** (0.316)
New CAD	0.026 (0.205)	-0.124 (0.178)	-0.051 (0.217)
New Tech Training	-0.536* (0.285)	-0.450* (0.244)	-0.053 (0.301)
New Basic Training	-0.534 (0.328)	0.099 (0.280)	-0.399 (0.350)
New Teams	0.324 (0.234)	0.238 (0.196)	-0.358 (0.247)
Observations	145	140	150
R-Squared	0.15	0.21	0.08

[a] All regressions include the age of the plant, the change in the number of shopfloor employees at the plant and whether the plant is unionized.

Standard errors in parentheses
* significant at 10%; ** significant at 5%; *** significant at 1%