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Technology Adoption, Learning by Doing, and Productivity:A Study of Steel Refining Furnaces

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Abstract

Models of vintage-capital learning by doing predict an initial fall in productivity after the introduction of new technology. This paper examines the impact of new technology on plant-level productivity in the Japanese steel industry in the 1950s and 1960s. The introduction of the basic oxygen furnace was the greatest breakthrough in the steel refining process in the last century. We estimate production function, taking account of the differences in technology between the refining furnaces owned by a plant. Estimation results indicate that a more productive plant was likely to adopt the new technology, and that the adoption would be timed to occur right after the peak of the productivity level achieved with the old technology. We have found that the adoption of the new technology primarily accounted not only for the industry's productivity slowdown in the early 1960s, but also for the industry's remarkable growth in the post-war period. These results are robust to endogeneity in the choice of input and technology.

Keywords: learning by doing; vintage capital; technology adoption; TFP; endogeneity; sample selection

JEL: D24, L61, O14, O33.

1 Introduction

An important source of the U.S. productivity slowdown observed around 1973 and afterwards was the introduction of new technology embodied in capital goods (Greenwood and Jovanovic, 2001). Numerous theoretical models of technology adoption indicate that when plants switch to new

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production technology, their productivity initially falls and thereafter gradually rises. The initial productivity drop implies that the experience obtained through operating old technology does not fully transfer to new technology. The rise in productivity suggests that learning by doing occurs after the technology adoption.[1] Theoretical research and simulation results have indicated that the diffusion of new technology can explain a significant part of productivity slowdown observed in the U.S. and other industrial countries (surveyed in Greenwood and Jovanovic, 2001). On the other hand, there is a severe lack of empirical research identifying the existence of and measures the magnitude of the impact of new technology adoption on productivity. Such empirical research would help us to assess the validity of the models used in the literature to quantify aggregate productivity growth as propelled by technological improvement embodied in capital. Accurate measurement of the productivity impact requires plant-level information that identifies the vintage of capital investment. The data set for such a study should distinguish between the investment that reflects the *adoption* of *new* technology, and that which reflects the *expansion* of *old* technology.

This paper investigates the effects on productivity of new technology adoption, using the plant-level data pertaining to the Japanese steel industry. In the 1950s and 1960s, many firms updated their refining furnace technology, shifting from the conventional open-hearth furnace (OHF) to the basic oxygen furnace (BOF). The share of output produced by BOF expanded from 4.1% in 1957 to 83.4% in 1968, a diffusion rate faster than that found in other innovations.[2] The introduction of the BOF was praised as "unquestionably one of the greatest technological breakthroughs in the steel industry during the twentieth century" (Hogan, 1971: 1543), and provides us with an ideal case for studying the impact of new technology adoption. The period of rapid spread of BOF technology interestingly coincides with that of the remarkable growth Japan experienced after the devastation of the World War II. The steel industry, in particular, expanded its production more than fourfold over the decade between 1953 and 1964, raising Japan to the status of the world's largest steel exporter in 1969. Our unique furnace/plant-level data set covers the inputs and output of each furnace type, timing and size of new capital installation, and old capacity expansion. The data let us estimate production function by furnace technology, and measure the change in productivity and output growth before and after the adoption of the new technology.

Our estimation results indicate a greater than 14 percent decline in productivity caused by the obsolescence of OHF-specific experience, upon adoption of BOF technology. The rapid diffusion of BOF may initially appear at odds with the finding of the large obsolescence of experience with old technology. Jovanovic and Nyarko (1996) and Parente (1994) have indeed proposed models whereby

[1] Greenwood and Jovanovic (2001) point out that R&D investment is another source of productivity gains. However, this factor probably was insignificant in the case of the Japanese steel industry, because the Japanese merely adopted, but did not *develop* the new furnace technology.

[2] See, for example, Gruber (1991).

new technology diffusion slows with an increase in technology adoption cost. We have noted that the rapid diffusion of BOF in Japan was due to the concerted efforts of the Japanese Ministry of International Trade and Industry (MITI) of Japan to hold down the license fee for BOF use. This government intervention lowered a barrier to Japanese steel makers accessing the more efficient technology, and ultimately helped them achieve the steel "miracle" of the 1950s and 1960s. This paper indeed finds that had the BOF not been adopted, output growth would have been averaged only 2.3 percent annually, in contrast with the actual 15.2 percent growth achieved from 1957 to 1968.

Two empirical studies examine the effect of new technologies on productivity. Huggett and Ospina (2001) analyze output growth using data pertaining to major equipment purchases from a plant-level survey of the Colombian manufacturing sector. Sakellaris (2004) studies the period of rapid capital adjustment in U.S. Census data. Both papers use a large adjustment in capital as a proxy for new technology adoption. This method is imperfect, being unable to differentiate new technology adoption from old technology acquisition, and thus unable to identify vintage-specific learning by doing. This paper indeed finds that in examining the history of the Japanese steel industry, incorporating the difference in capital vintage is essential in production function estimation, and that neglecting to do so overestimates total factor productivity (TFP) growth. The present paper makes two additional extensions to this literature. First, we control for omitted variable bias in the construction of TFP, and also deal with possible selection bias due to the choice of technology. Controlling for these econometric problems, we find that more productive plants were more likely to adopt new technology, doing so right after their productivity levels peaked with the old technology. Second, our measure of output and input are in terms of quantity rather than value added. We are thus free of a "deflator" problem in estimating the production function. This problem could be severe in studying the Japanese steel market, in which only a handful of dominant major firms operated under minimal competitive pressure from abroad. As a result, this paper identifies a productivity decline of greater than 14 percent upon new technology adoption, whereas Huggett and Ospina (2001) and Sakellaris (2004) find the ranges of 1.7-4 percent, and 3-9 percent, respectively.

This paper also contributes to the literature concerning learning by doing through conducting production function estimation. Few empirical studies have examined whether learning persists within organizations, and the concept of organizational forgetting – the hypothesis that a firm's knowledge stock depreciates over time – has been proposed. Argote, Beckman, and Epple (1990) and Benkard (2000) find support for this hypothesis as it applies to shipbuilding during World War II, and in commercial aircraft production, respectively. Although these papers informally attribute the forgetting to rapid job turnover or highly variable production costs, no papers on organizational forgetting identify the actual sources of the forgetting. If an instance of technology adoption indeed leads to a fall in productivity, it could be considered as a source of organizational forgetting. This paper's contribution to the literature is to focus exclusively on one possible influence on organizational forgetting, i.e., new technology adoption, and formally assess its impact on productivity.

The paper is organized as follows. Section 2 documents the features of the Japanese steel market in the 1950s and 1960s that have an important bearing on the subsequent modeling and estimation framework. The section emphasizes the importance of technology-specific learning in furnace use, and describes the steel refining process. Section 3 delineates the estimation framework used to measure productivity in the refining stage of steel production. Section 4 presents the estimation results. The learning-by-doing effect is found to be significant, and estimates obtained by the proxy method indicate the successful elimination of endogeneity. Based on the estimation results, Section 5 analyzes industry and plant-level productivity, and examines the impact of the new technology adoption on TFP and industry output. Section 6 concludes, and is followed by technical and data appendices.

2 An Overview of the Post-war Japanese Steel Market

Japan's remarkable growth from the 1950s through the 1970s has been well studied by economists and policy makers. Japan's experience is a prototype of the so-called "flying goose model," in which industries experienced rapid growth one after another, with a lead industry providing external benefits to subsequent industries, helping them take off. In the context, the steel industry was the "lead goose" in Japan's marvelous growth after the World War II, followed by the TV and automobile industries.

Most Japanese steel in the early 1950s was produced by integrated steel manufacturers. Integrated steel works transform raw materials (iron ore and coking coal) into pig iron in a blast furnace. Pig iron is then transformed into crude steel in a second furnace by removing carbon and other elements. The prevalent technology used in this second, or "refining," stage at the time was the open-hearth furnace (OHF), which blows air from the bottom of a steel shell through the molten pig iron. The air raises the temperature in the pig iron and oxidizes the carbon in it. In the late 1950s the OHF began loosing ground rapidly, being replaced by the basic oxygen furnace (BOF). According to Hogan (1971), the introduction of the BOF was "unquestionably one of the greatest technological breakthroughs in the steel industry during the twentieth century" (p. 1543). A major advantage of the BOF was that it refined molten iron and scrap charge into steel in about 45 minutes, a sharp reduction from the 6 hours normally required by the OHF at the time. Furthermore energy costs declined appreciably with use of the BOF. Electricity was necessary fuel to operate the furnaces. Table 2 shows that the average electricity consumption per million ton of steel production with the BOF was 20 kWh, whereas 30 kWh for the OHF and 890 kWh for the electric furnace. Crude oil was used mostly for the OHF, and is thus included in the estimation explained in Section 4.

Use of the electric furnace (EF) became widespread with the assurance of adequate electric power at industrial rates. The size of the EF was small: according to our data, on average, the EF was one quarter the size of the OHF, and one fifth the size of the BOF (Table 2). The EF used mostly scrap as its material input, and did not require molten pig iron directly from a blast furnace. The EF thus made it possible for non-integrated companies (i.e., the companies with no blast furnace) to enter the steel industry with minimal capital investment, and for integrated companies to expand production capacity incrementally. These three types of steel refining furnaces produced crude steel of homogenous quality. While we are mostly interested in the OHF and BOF, our estimation also incorporates the EF so as not to select biased samples regarding this dimension.

Upon the adoption of BOF, the MITI formed a group of Japanese steel makers, and negotiated over a technology license as a single buyer with the patent holder, Brassert Oxygen Technik, A.G. An agreement was reached whereby a set fee of $1.4 million would be collectively paid for the technology by all the Japanese adopting firms. This licensing fee turned out to be incredibly cheap for the Japanese. According to Lynn (1982):

> Each firm was to be assessed a constantly declining royalty per ton of steel, so that each would have paid the same amount per ton of steel produced by the time the license expired in 1970. [...] During the fourteen-year period of the license, Japan produced approximately 320 million tons of BOF steel—so the license cost per ton of steel produced came to about 0.36 cents. Firms in North America were asked to pay royalties ranging from 15 cents to 25 cents and more per ton of steel produced. (83-84)

Table 1 presents the number of plants and output share, by furnace technology, further breaking down the data by firm size. The top six firms were Yawata, Fuji, Nihon Kokan, Kawasaki, Sumitomo, and Kobe in order of production share. This order did not change during the 1956-1968 study period, the period in which most BOF adoption occurred in the Japanese market. Most plants owned multiple furnaces of the same vintage: Table 2 indicates more than 4 OHF and 2 BOF furnaces per plant. We account for this feature of the data in the estimation.

Looking at the material presented in Table 1, we note that firms owned multiple plants, and that plants operated more than one refining technology. According to Table 1, the average number of firms in the industry over the 1956-1968 period was 35; the average number of plants was 58, and the average plant had 1.4 furnace types. The share of the output produced by the largest firms rose from 78 to 86 percent in this period. The six large firms owned more plants and furnaces, and experienced a more drastic output shift from OHF to BOF technology: the BOF share of the industry output rose from 4.5 to 83.4 percent, mostly substituting for the decline of the OHF share from 87.2 to 7.5 percent. This BOF diffusion rate appears fast, relative to those of other innovations reported in the literature. For example, Jovanovic and Lach (1996) cites a study of 265 innovations that found that it took 41 years on average for the output share of a new technology to rise from 10 percent to 90 percent – a marked contrast to 15 years for our Japanese BOF case. Since each plant presumably chose the most profitable technology to maximize the discounted stream of profits, our observation of BOF diffusion may necessitate our correcting for self-selection in technology choice in the production function estimation. About 80 percent of the EF output is attributed to smaller firms, as expected in view of EF capacity. Four firms ceased to exist in this thirteen-year period, two of which were acquired by large firms. The infrequent exiting of firms from the sample leads us to believe that the sample selection caused by plants exit is not a major concern regarding our data.

Although one may think that a furnace is not a very sophisticated piece of equipment, Hogan (1971) and Japan Steel Association (1971) note that it was only through extensive furnace use that detailed knowledge was gained about furnace operation, maintenance frequency, and overhaul requirements. In a number of instances, closer control of molten metal temperature through better sampling was necessary to improve fuel efficiency in furnace operation by reducing variations between heats. Experiential knowledge based on OHF operation was largely inadequate to anticipate the reliability of the BOF or EF operations (Lynn, 1982: 56, 133). In addition, the efficiency of furnace operation after prolonged use or with aging was difficult to predict: frequent sampling during the heats helped maintain efficient production of crude steel, and led to new practices that increased furnace productivity. The steel production experience described above suggests the existence of learning by doing, or learning by using (Rosenberg, 1982) in the operation of a particular furnace technology. The learning experience gained in operating a particular furnace was not likely transferable to other furnace technologies, and since efficient operation depends on many plant-specific conditions, knowledge through learning activity may also have been plant specific, and not shared by others.[3] We test this spillover hypothesis in Section 4.

[3] Japanese steel makers attempted to combine their efforts to control furnace operations by creating an integrated computerized system in the 1960s, finally succeeding at this in 1973 (Japan Industry Newspaper, 16 October 1976). This example indicates how knowledge transfer between firms was still problematic in the study period. Ohashi (2004) notes a similar finding regarding blast-furnace operations in the Japanese steel market.

3 Measuring Productivity

Our empirical goal is to compare the productivity between plants and across time, while explicitly considering differences in furnace technology. To do so, we need estimates from the production function that describes the steel refining process. Considering that the three furnace technologies, OHF, BOF, and EF, feature substantially different operational characteristics, we allow for production function parameters to differ in terms of technology. The description of the industry in the previous section reveals that learning by doing was an important feature of furnace operations. The production function thus incorporates learning by doing, as well as other control variables such as capacity size and input measure.

Learning by doing explains why extensive use of a particular furnace type leads to more efficient production. Section 2 describes how the knowledge gained through learning by doing was technology specific, i.e., geared to a specific furnace type, and was not transferable to the operation of the other types of furnaces. Lynn (1982) also describes how "hard-gained skills were made obsolete with demise of the open hearth" and by the introduction of the BOF. The learning by doing process, however, is not directly observable, and is thus difficult to measure. Following the treatment in the literature (for example, Spence, 1984), we use cumulative output level as a proxy for a plant's learning level for a particular technology s (s is either OHF, BOF, or EF). Let Z_i^s be plant i's experience with furnace s. The transfer of the experience is described by $Z_{it}^s = Z_{it-1}^s + q_{it-1}^s$ in which q_{it-1}^s is steel output of furnace s in plant i at time $t-1$. Although the production knowledge was not shared across s, the knowledge possibly spilled over between plants within a firm. We thus allow for the possibility of within-firm spillover in Section 4. The plant-level data are first available for 1947, so we assume that furnace experience begins to accumulate after the war, taking the experience in 1946 to be zero (i.e., $Z_{i,1946}^s = 0$). Note that we chose to start the study period in 1957, when the steel production had recovered to the wartime peak achieved in 1943 (See Figure 1). Our estimate of the learning effects are thus based on the knowledge level newly acquired in the postwar period.

All three types of furnaces studied produce crude steel, a homogeneous product. Our econometric model of the production function assumes the following Cobb-Douglas form (all variables are in logarithmic form):

$$y_{it}^s = x_{it}^s \beta_x^s + k_{it}^s \beta_k^s + z_{it}^s \beta_z^s + \tau^s + \lambda_t + \omega_{it}^s + \varepsilon_{it}^s, \tag{1}$$

where y_{it}^s is annual output (in tons) for furnace s at plant i in year t. The production function comprises a number of input variables. The vector of fuels and labor input is x_{it}^s: all furnaces used electricity as an energy source, and the OHF used oil in addition. The major inputs for steel making were molten pig iron and scrap, but we do not include them in (1). The steel-production process transforms pig iron and scrap directly into crude steel, so the inputs and output have a one-to-one mapping: in this paper, we are more interested in analyzing how efficiently the furnaces completed this transformation process. The capacity size of furnace s is indicated by k_{it}^s, and z_{it}^s is the logarithm of Z_{it}^s. While we do not have precise data on capacity utilization, we expect that the electricity consumption in x_{it}^s approximates the variable well. It is important to include z_{it}^s in (1). If we do not have this regressor, the coefficients of k_{it}^s would be overestimated, since we find high correlation between k_{it}^s and z_{it}^s (the correlation coefficient is 0.65 on average across s). Of course, if the vintage-capital learning by doing were not important in steel refining, we would not observe significance in β_z^s. The base model also contains technology- and year-specific components (τ^s and λ_t, respectively). We use dummies to control for the specific components. The year dummies control for aggregate industry shocks in the variables. The inclusion of technology dummies serves to control for efficiency differences of production. Omitted variables add to the content of the last two terms in (1), and create the likely source of an upward bias in β_x^s, as discussed below.

Note that y_{it}^s is measured in terms of output quantity, not value added. Many studies use value added, as deflated by a common industry deflator, under the implicit assumption that a condition of perfect competition holds for the product market. If this assumption is violated, it is difficult to obtain unbiased estimates of production-function parameters without use of quantity measures of output (Klette and Griliches, 1996).

The production function (1) contains two mean-zero errors, which are not known by the econometrician. We divide the errors into two, depending on whether or not they are known by the producer. We assume that ω_{it}^s represents productivity as known by the producer, and that ε_{it}^s is the error introduced by measurement, data collection, and computational procedure that is not foreseen by the producer. Productivity unobserved by the econometrician may create two endogeneity problems: endogeneity in input choice, and endogeneity in technology choice.

Endogeneity in input choice arises when producers adjust the amount of material inputs (fuel and labor in our application) by their efficiency differences in ω_{it}^s. For example, those plants that perceive higher productivity might have used more fuels. The ordinary least squared (OLS) method, which fails to account for such correlation, would generate biased estimates. A common response to the endogeneity problem is to treat unobserved productivity differences between plants as constant over the study period, using fixed effects to control for the differences. This within estimator uses deviation from plant-specific means in the OLS estimation. While it deals with permanent differences in unobservables, the fixed effect approach is known to exacerbate other misspecification problems such as errors in variables. Furthermore, this approach cannot control for unobserved plant productivity that varies over time.

To protect against this possible problem in the fixed effect approach, we employ the method recently proposed by Levinsohn and Petrin (hereafter L-P, 2003). The method is to create a proxy for ω_{it}^s by bringing in an input demand equation from outside the production function framework: we refer to this as the proxy method in this paper. It does not assume that plant productivity difference is fixed over time. The original idea of this proxy method, attributed to Olley and Pakes (1996), uses an investment decision function instead of an input demand equation as a proxy for productivity. This investment proxy, however, is not valid for 70 percent of our data in which plants reported no investment made (see Table 3). This feature of our data causes a problem in considering a proxy for ω_{it}^s using Olley and Pakes's (1996) technique. The infrequency of investment revealed in our data is perhaps because steel-production technology involves substantial capital adjustment costs.[4] Use of material inputs, instead of investment, must satisfy the condition, because furnace operation always requires pig iron and scrap for production. Indeed Table 3 almost always records the use of material inputs, for which we use the sum of pig iron and scrap in tons. Moreover, an efficient furnace wastes less material inputs in the refining process, so the material input consumption is correlated with productivity. This correlation is concurrent particularly with OHF and BOF use, because molten pig iron, discharged from blast furnaces, cannot be stocked. We follow the estimation recipe described in L-P (2003, Appendix C) in performing the proxy method. Our approach differs from that of the cited method in that we have two capital coefficients (capacity size and experience), and in that we estimate production function by furnace technology. Since the use of this method has become widespread in the literature of production function estimation (for example, Pavcnik, 2002; Kasahara and Rodrigue, 2004), we defer further details of our estimation procedure to the technical appendix.

Endogeneity (or self selection) in technology choice arises when a firm's decision as to which furnace technology to use is not random, but correlates with productivity, ω_{it}^s. The severity of selection bias depends on the magnitude of productivity difference between plants that do and do not adopt the new technology. In theory, two hypotheses exist as to the relationship between plant productivity and technology adoption. One is that more productive plants are more likely to adopt new technology. For example, Caselli (1999) argues that skilled biased technology tends to be adopted by plants with high human capital levels, because skill and technology are complementary under strong learning-by-doing conditions. Since plants with more skilled workers are more productive, this hypothesis implies that productive plants are more likely to adopt the BOF.[5] The alternative hypothesis is related to technology leapfrogging. Jovanovic and Nyarko (1996), for example, finds an "overtaking" equilibrium where less-productive plants switch to a better technology more often

[4] Infrequent investment is also observed in the U.S. manufacturing sector (Doms and Dunne, 1998).

[5] As we discuss in Section 4 and in the Data appendix, our data set is not suitable for testing a hypothesis concerning wage premium and human capital. The purpose of our discussion here is to illustrate the importance of controlling for self selection in the choice of technology.

than productive ones. In their model, productive plants are experienced with old and familiar technology, while less-productive plants are less attached to the technology. This extensive experience prevents productive plants from adopting a new technology, while less productive ones are willing to try it. This hypothesis suggests that less-productive plants are likely to adopt the BOF. The direction and severity of the selection bias is an empirical question. Thus our specification corrects for this selectivity of furnace technology using sample selection technique.

4 Estimation Results

This section applies the estimation method described in the previous section to the data set. The production function (1) is specified by furnace vintage at the plant level. We pool the data pertaining to all three furnace types and estimate a system for the furnace production functions, allowing for input coefficients to differ in terms of vintage. The next section uses the estimates obtained here to construct measures of furnace- and plant-level productivity, and analyzes changes in the productivity distribution arising from the adoption of BOF technology. Summary statistics pertaining to variables used for the estimation appear in Table 4, and data sources are available in the Appendix. Data concerning labor input is worth mentioning. Labor input is the total number of man hours, constructed from the number of plant-level workers multiplied by the actual average hours worked by workers at the firm level. The labor data are not available by furnace vintage. The variable thus mixes the employment of non-production, skilled, and unskilled production workers.[6]

Table 4 presents five estimation results, based on the OLS (column A), plant fixed effect (column B; hereafter FE), and proxy (columns C, D, and E) methods. The base model (1) assumes plant-specific learning in the experience variable, and the specification (D) tests this assumption against the hypothesis of learning spillover between plants under the same ownership. Specifications (B), (C), and (D) concern endogeneity in input choice, and specification (E) adds the concern of self-selection bias in technology choice. All specifications in Table 4 use technology and year fixed effects. We cannot separately identify ω_{it}^{s} and ε_{it}^{s} in the OLS and FE methods, but we can in the proxy method. The upper part of the table reports estimates of the regression coefficients. Our inference is based on heteroskedasticity-robust standard errors. The five results indicate that the models fit the data well. The measure of adjusted R^2 is quite high, and the J-statistics for the proxy method support the validity of the instruments, conditional on there being a set of valid instruments that just identify the model. We also test the hypothesis that the production coefficients are the same across the three vintages. The results of the Chi-square test presented in the table would

[6]The results reported in this section are robust to the exclusion of the labor variable. The results are available upon request. Wage data (not used in this paper, available from Japan Iron and Steel Federation, 1955-1970, b) are available only at the industry level, and mix skilled and unskilled workers.

reject the hypothesis of homogenous technology among the three furnaces for most specifications, and thus justify our specifications that allow for coefficients to differ by furnace vintage.

Most of the estimates in (A) are precisely estimated; however, we are concerned that endogeneity in input choice may lead to a positive correlation between the intermediate inputs (labor, electricity, and oil) and the current unobserved productivity. The resulting upward bias in the input coefficients could be severe, as input consumption is easily adjusted to productivity. Furthermore, if inputs and other state variables, capacity size and vintage-specific experience, are positively correlated, the coefficients of the two state variables are shown to be underestimated in the OLS estimation. The FE estimator accounts for the bias as long as furnace and plant unobserved productivity is constant over time. It is, however, hard to see from (B) that the bias in the input coefficients is corrected (or that the bias might not have mattered at all in A). Only the electricity and capital coefficients of EF move in the expected direction from (B) to (A).

To account for time-varying productivity, we have implemented the proxy method of L-P (2003). The estimation method is detailed in the technical appendix. The estimates of the coefficients reported in (C) significantly differ from either the OLS or FE results. The input coefficients (labor, electricity, and oil) are now much lower than those in (A) and (B), indicating successful elimination of endogeneity. In fact, they are all economically and statistically not significant. The coefficients of capacity size and experience are precisely estimated, and corrected to the direction predicted by the theory: since the larger furnace consumed more fuel, the endogeneity of the fuel variables attenuates the contributions of capacity and experience to productivity. The proxy method yields estimates of capacity size (experience) that are on average 10.0 (10.7) percent higher than those from obtained using the OLS method, and 18.0 (20.6) higher than those obtained from the FE method.

The coefficients of vintage-specific capacity variables are all less than one, and this may indicate the existence of decreasing returns to scale. This point, however, could be misleading, because we assume the constant returns to scale across multiple furnaces of the same technology at the plant level; we do not take into account the fact that capacity size increases only with the installation of new furnaces. Table 2 indeed indicates that most plants owned multiple furnaces. We have incorporated the number of furnaces in the estimation, and will discuss the implications for returns to scale in this section. The learning parameter in (C) indicates that the learning rate for the OHF was the highest at 37.4 percent, followed by 25.7 percent for the EF and 15.8 for the BOF. The learning rate is the magnitude of the output increase with a doubling of experience, and is calculated as $2^{\beta_z} - 1$. Ghemawat (1985) reviewed the learning-by-doing literature, and found that the learning rates for the vast majority of products fell in the 11-21 percent range. Thus the BOF and EF attained slightly higher than average learning rates under (C).

The first three results are based on the assumption that vintage-specific experience is shared only within a plant. It is possible that the experience may spill over, not only within a plant, but also among plants owned by the same firm. To test this spillover hypothesis, we estimate the following production function:

$$y_{it}^{s} = x_{it}^{s}\beta_{x}^{s} + k_{it}^{s}\beta_{k}^{s} + z_{it}^{s}\beta_{z}^{s} + \beta_{z\_others}^{s}\ln\left(\sum_{j\in\Phi_f,\, j\neq i} Z_{j,t}^{s}\right) + \tau^{s} + \lambda_t + \omega_{it}^{s} + \varepsilon_{it}^{s},$$

where we add to (1) the intra-firm spillover variables, $\sum_{j\in\Phi_f,\, j\neq i} Z_{j,t}^{s}$ (for $j \in \Phi_f$, where Φ_f is a set of plants owned by firm f), representing the cumulative outputs by technology type of the other plants ($j \neq i$) owned by the same firm f. Note that all variables in (1) are in logarithmic form. If the learning spillover has an important impact on productivity, we should observe it in the coefficients of the new variables. We estimate this model using the proxy method, and the results are presented under (D) in Table 4. The estimates of $\beta_{z\_others}^{s}$ are neither statistically nor economically significant for all values of s, and the other coefficients barely change from those in (C). The FE estimates also generate insignificant spillover coefficients (not reported in the table). We conjecture that many plant-specific conditions, such as furnace age and usage intensity, mattered in the efficient operation of furnace, and that they hindered other plants from sharing the experience.[7]

The final estimation result, (E) in Table 4, corrects for selectivity in technology choice. The choice of furnace technology could be endogenous if a persistent relationship exists between plant productivity and choice of technology. This concern would make both capacity and experience correlate with the error in the equation. We have modified the Heckit correction procedure for the sample selection. The modification, described in the technical appendix, is needed because we have four states for the furnace technology choice: BOF, OHF, EF, and exit. We assume ordered probit in the selection stage, and add a new correction term for each technology.[8]

The estimates of the newly included regressors are not significant, indicating that the selection problem is not severe. Indeed, the magnitude of differences in the estimated elasticities of capacity size and experience between the results in (C) and (E) are not significantly different from zero. We thus conclude that the selection problem is less severe, probably because exit from OHF or entry into EF or BOF are often successes for plants, rather than failures.[9] We also check the selectivity

[7] Industry-level learning by doing, if exists, would be already controlled for by the year fixed effect, λ_t.

[8] The validity of the selection model relies on the joint normal distribution. To check the robustness of result (E) to this distributional assumption, we re-estimated the production function, replacing the ordered probit with a multinomial logit model as a selection rule. The advantage of the multinomial logit model is that the distribution does not impose the ordering of the technology states. Since we were unaware of the closed solution for the modified Heckit procedure for the multinomial logit, we approximated the three Heckit terms using a third-order polynomial with a full set of interactions of the estimated logit-choice probabilities. We found that the estimated production function parameters are similar to those obtained under (E). The results are available on request.

[9] The selection-bias correction was also only minimally important in Griliches and Mairesse (1998).

bias using the FE approach, and again conclude that the problem appears to be minor for our data (The results are available from the authors on request).[10]

The specifications in Table 4 do not explicitly consider discontinuity in the capacity size and experience variables, and assume constant returns to scale across multiple furnaces of the same technology owned by plant. More than 80 percent of the plants possessed multiple furnaces of the same vintage, and capacity size in particular changes only with the number of furnaces operated by a plant. To test whether shifting from n- to $n+1$ furnace operations (where n is an integer greater than zero) changes the capital and experience elasticities of productivity, we have estimated different coefficients of capital and experience by number of furnace. Due to the small sample size, we shall employ only three plant operation cases: zero-furnace operations, one- or two-furnace operations, and operations with two or more furnaces. Two estimation results are reported in Table 5. Both specifications use the proxy method, and column (G) adds the selectivity control of technology by the same method as was used in (E). We tried to augment control for the number of furnaces by using the sample selection technique, but did not succeed mainly because the number of observations in each state became too small. We thus controlled only for technology choice in (G). As with the results presented in Table 4, the selectivity bias appears to be minor. Table 5 finds decreasing returns to scale for physical capital, and increasing returns to scale for experience. The results make sense in that the experience embodied in furnace operators is easily applicable to all furnaces of the same technology, while it is difficult to obtain economies of scale in physical capacity across different types of furnaces. However, the standard errors reported at the bottom of Table 5 indicate that neither of the returns-to-scale estimates are statistically significant. The subsequent sections thus use the estimation results appearing in Table 4 as base estimates.[11]

To obtain a sense of how the model fits the data, we compare the actual and predicted industry outputs and furnace-type production shares over the study period. The left-hand side of Table 6 presents predictions based on the (C) estimates, while the right-hand side presents the actual data.[12] The difference between the actual and predicted values indicate the presence of ε_{it}^{s}. As we discuss in the technical appendix, we use the input data from 1956 to control for endogeneity of inputs. Thus our estimates in the table and in subsequent sections start in 1957. To save space, we have listed only the production shares of the largest and the smallest furnaces by vintage at the end of the sample period. Table 6 shows that the model explains the data well, suggesting

[10] Note that the estimates of β_x^s in (C) and (D) are the same. This is because the spillover coefficient is calculated after the estimates of β_x^s are obtained. See appendix A1 for details of the estimation procedure.

[11] The idea of incorporating the number of furnaces in the production function is similar to that of Bertin, Bresnahan, and Raff (1996) in its estimation of labor productivity. Our paper differs from the above work in that we are interested in the adoption of new technology in the estimation of TFP and vintage-specific learning by doing.

[12] Use of the results (E) or (F) generates similar results.

that the productivity unobserved to the producers was small. Industry outputs are predicted fairly accurately, and there is no noticeable bias in the production shares of the dominant technologies, OHF and BOF.

5 Productivity and New Technology

This section, comprising two subsections, analyzes the TFP of the post-war Japanese steel industry using the estimation results presented in the previous section. Section 5.1 analyzes implications for aggregate industry-level productivity. A productivity slowdown was observed in the 1960s, when plants adopted BOF refining technology. This suggests that factor accumulation was the leading contributor to the growth of the Japanese steel industry. To look for the source of the productivity slowdown, in Section 5.2 we decompose the industry productivity down to the furnace and plant level, finding that the loss of OHF experience accounted for the productivity slowdown observed at the industry level. This section also analyzes hypothetical steel output had plants not adopted the BOF. We find that the new technology indeed contributed to expanded steel production: had plants stuck with the old technology, output would have increased only 2.3 percent annually, far below the actual 15.8 percent output growth. This result was explained by our findings that BOF produced more steel than did OHF using the same amount of inputs, and that the capital-size efficiency of BOF is far larger than the loss of experience upon BOF adoption.

5.1 Industry-level Productivity

We first present aggregated industry productivity for the 1957-1968 period.[13] Our productivity measure comprises the contributions of learning by doing (captured by $z^s_{it}\beta^s_z$) and of disembodied technical progress. This latter is represented by the sum of the estimates of τ^s, λ_t and ω^s_{it} for (B) and the proxy method, where ω^s_{it} is the plant fixed effect for (B). Note that for the OLS estimate we cannot distinguish between ω^s_{it} and ε^s_{it} in the estimation. We thus use $y^s_{it} - x^s_{it}\beta^s_x - k^s_{it}\beta^s_k$ as the estimated productivity for the OLS.[14]

Table 7 presents annual changes in aggregated industry productivity growth. Productivity is calculated annually as the share-weighted average of furnace and plant productivity. The table shows two blocks of TFP estimates. We obtain the first block by ignoring the difference in furnace vintage (i.e., we estimate (1) without the subscript s). These TFP estimates are based on the

[13] As discussed in the previous section and in the technical appendix, our estimates start in 1957, because the 1956 data are used as instruments in the estimation. See the technical appendix for details.

[14] The proxy method uses $z^s_{it}\beta^s_z + \tau^s + \lambda_t + \omega^s_{it}$ as a productivity measure, and thus the productivity does not contain ε^s_{it}. The use of $y^s_{it} - x^s_{it}\beta^s_x - k^s_{it}\beta^s_k$ also generates a similar TFP result. This finding is not surprising, as Table 6 shows a good model fit to the data.

conventional assumption of homogenous capital. Although the Chi-squared tests presented in Table 4 rejected the homogeneity assumption, the TFP estimates provide a useful reference for our later discussion. The second block of TFP estimates recognizes the difference in capital vintage, and is constructed from estimates (A), (B), and (C) presented in Table 4. Each block presents three TFP estimates, computed by either the OLS, FE, or proxy methods described in Section 3.

Table 7 shows that conventional estimates produce TFP values about twice as large as those produced by vintage-capital estimates. Conventional TFP annual growth rates range from 13.5 to 15.2 percent, close to the actual output growth of 17.0 percent. The output growth appears slow in some periods, three of which (1957-1958, 1961-1962, and 1967-1968) mark known recessions in Japan. When accounting for vintage in steel technology, we find that estimated TFP growth is substantially reduced to the range from -1.12 to 7.27 percent, indicating a productivity slowdown, especially in the 1961–1963 period. Interestingly, the slowdown period roughly coincides with the time when the plants represented in the data updated their technology to the BOF, as shown in the second column in the table. The results in Table 7 suggest that factor accumulation was the leading factor in the growth of the Japanese steel industry.

To see productive efficiency by furnace type, we present TFP values and input contributions in Table 8. The TFP values are broken down into two productivity factors: one is learning by doing, and the other is disembodied technical progress. We realize that it is difficult to compare input contributions across furnace types because the amounts of inputs used vary by furnace type. We thus set the inputs of the different furnace types to be the same as the OHF inputs for each year to make the comparison possible. Thus our measure of input contribution in Table 8 is the mean value of $x_{it}^{OHF}\beta_x^s + k_{it}^{OHF}\beta_k^s$. Each productivity component (expressed logarithmically) is calculated annually as the share-weighted average of the plant productivity measure. The table reveals that the estimated contribution of disembodied technical progress is highest for the BOF: the estimated contribution of learning by doing is, however, highest for the OHF – the oldest technology. We also find that the inputs contribution is highest for the BOF, indicating that it is the most efficient steel refining technology in terms of input use, followed by the OHF, and the EF. This finding is consistent with the received wisdom described in Section 2.[15] Since the contribution of learning by doing to the TFP of BOF grows slowly, due to the small estimated coefficient of learning by doing reported in Table 4, we conjecture that plants must have suffered an initial productivity decline

[15] The measure of disembodied technical progress in Table 7 moves in accordance with technology progress as reported in the trade press. The utilization rate of one of the most efficient OHF process, which used oxygen, started to decline in 1961, when plants switched to the BOF. The contribution of disembodied technical progress in the BOF and EF meanwhile generally increased. For the BOF, two important improvements (the multi-hole lance and the OG system) were implemented in the period. Use of a large-capacity transformer is known to have improved EF production.

when shifting production to the BOF. The aggregated productivity displayed in Tables 7 and 8, however, does not tell us the exact source of the productivity slowdown observed in Table 7. The next subsection delves further into plant-level productivity in pursuit of the source of the slowdown.

5.2 Source and Implications of Productivity Slowdown

Table 9 shows the annual output shares and the share-weighted plant-level productivity. Sixty-six plants are represented in the data, and grouped by operating furnace type. The table divides the plants into two groups: those that kept using the old OHF technology, and those that adopted the new technology at some point in the study period. The first group comprises five subgroups depending on the types of furnaces owned, while the second group comprises two such subgroups. Plants that used OHF technology and added EF during the study period are placed in category (G9), while those that added EF prior to the study period are placed in category (B9) in Table 9.

The table shows that the average productivity of adopting plants (column H9) is higher than that of non-adopting plants (column E9). This is indicated by fact that the ratio of the productivity indices, shown in column (I9), is greater than one. This ratio shrinks from greater than 2 to 1.5 over the decade, because of the learning-by-doing effect: a BOF-adopting plant loses OHF-specific experience upon new technology adoption, while a non-adopting plant continues to accumulate experience. More than 70 percent of the OHF plants had newly added BOF in the study period (under F9), attaining the highest average productivity. Five new plants had installed BOF only (D9), but they do not account for the productivity slowdown displayed in Table 7. The plants that had newly installed EF (shown in G9) had lower productivity than those with OHF throughout the period (A9). It is likely that the plants in (G9) are those that were not efficient enough to maintain a large facility, and thus downsized by installing EF, as discussed in Section 2.

Considering their large production share, the main culprits in the TFP slowdown observed in Table 7 are the plants in category (F9). We will take a closer look at those thirteen plants that adopted BOF, and analyze the impact of the new technology adoption on their plant-level productivity. Figure 2 shows the changes in average productivity among the thirteen plants by year elapsed from BOF adoption. The horizontal axis indicates the number of years passed after BOF adoption, and thus the negative numbers indicate the number of years during which plants used the OHF before adopting the BOF. We show four different estimates of the productivity, constructed using the (A), (B), (C), and (E) estimates from Table 4. To facilitate comparison among the four productivity estimates, we normalize them (logarithmically) to be 100 at time 0, when the BOF was adopted. Figure 2 indicates that the adopting plants' productivity rapidly rises with the OHF, and then declines, followed by the adoption of BOF. This indicates that managers of the adopting plants may have timed the adoption, based on the TFP of their old vintage technology:

once they observed that the TFP of the OHF had begun to decline, the managers installed the new BOF technology. At the point of BOF adoption, productivity dropped by between 13.9 and 58.1 percent, based on the FE and the proxy estimates, respectively.[16]

This productivity drop is primarily due to the loss of OHF-specific experience. Our growth accounting, based on the proxy estimates, indicates that the TFP decline of -0.943 can be decomposed into two components: the change in learning by doing (-2.367), and the change in disembodied technical progress (1.423). Plant productivity gradually rose after BOF adoption, but it might have taken time before it overtook the productivity level previously achieved by the OHF: the FE estimates indicate that it would have taken three years.[17] This estimated number of years for the productivity catchup is small in comparison with calibration results presented in the literature. Greenwood and Jovanovic (2001), for example, finds that the advent of information technology sets labor productivity back, and that it takes about thirty years to return to its pre-IT level. One might expect that a general purpose technology would take longer to diffuse than a specific technology such as the one dealt with in this paper.

One might infer from the large loss of experience acquired with the OHF that the BOF diffusion rate must have been slower. In deciding when to adopt the new technology, a plant must have compared the future benefit of adopting the BOF with the cost of losing the value of the old experience upon the adoption. Experience with the old and familiar technology must have hindered a plant from updating its furnaces to the BOF type, suggesting a slower BOF diffusion. On the contrary, Table 1 indicates that BOF diffused rapidly, as discussed in Section 2.

Close study of trade journals provides an explanation that allows us to reconcile the seemingly contradicting observations of both rapid diffusion and large estimated experience loss. Section 2 mentioned that the MITI had succeeded in bargaining for a low license fee for the BOF use. The license cost per ton of steel production came to 0.36 cents for all Japanese companies, while firms in North America, which negotiated individually with other license holders, paid in the range of 15 to 25 cents. Previous literature has argued that this difference in license fees explains the slow BOF diffusion in the U.S. and the rapid diffusion in Japan (for example, Lynn, 1982).

[16] The TFP's obtained from the proxy method are five percent larger than those from the OLS and EF estimates. This TFP difference is primarily due to the insignificant estimate of the electricity consumption for OHF. Use of the 95-percent lower bound of this estimate produces the TFP, very close to the ones from the OLS and FE estimates. Considering that the electricity coefficient is precisely estimated in the OLS and FE, we feel rather comfortable with the finding of the 13.9-percent productivity fall.

[17] Figure 2 shows that all four types of TFP estimate behave in similar fashion after technology adoption, even though the (C) and (E) estimates are not similar to either the (A) or (B) estimates. We find that the increase in TFP due to the smaller BOF-electricity coefficient in (C) and (E) is offset by the decrease in TFP due to the larger BOF-capital-size coefficient, resulting in the TFP values in (C) and (E) being similar in level to those in (A) and (B).

MITI efforts to keep the royalty low was unlikely to have enhanced the welfare of the steel industry: we observed no evidence of spillover or externalities of the BOF adoption. However, it is evident that this intervention helped reduce the cost of BOF adoption, and encouraged Japanese steel makers to access a technology more productive than the OHF. Ultimately this government assistance may have helped the steel industry to achieve the remarkable growth of the 1950s and 1960s (in Figure 1). To analyze the extent to which BOF diffusion accounted for steel industry growth, we will perform the following simulation exercise. We ask how much steel would have been produced if BOF adopting plants had *not* installed the technology, but instead retained their old and familiar technology. Our simulation scenario assumes that those plants that adopted the BOF instead expanded their OHF capacity. The size and the timing of the capacity expansion are assumed to be the same as those of the actual BOF adoption. As well, the amounts of intermediate inputs (labor, electricity, and oil) used are assumed to be the same as were actually used in BOF adoption, and the estimate of the average disembodied productivity is used for the calculating the hypothetical OHF output.

To evaluate the validity of our simulation assumptions, one has to model the plant's behavior in terms of the choice of the amount of inputs and the timing and size of capacity expansion. Building such a model is, however, beyond the scope of this paper, so we base our simulation exercise on the exogenous assumptions presented here. The direction of the bias resulting from these exogenous assumptions could be downward: since the future of the technology is less uncertain with the OHF than with the BOF, plants would have expanded their old-technology capacity prior to the BOF adoption, and by a larger amount. This would make the hypothetical OHF output larger than the output achieved under the exogenous assumptions for any given year. Since the magnitude of the bias is difficult to assess using our framework, we should regard the following simulation results with caution. The results presented in Figure 3 indicate that the adoption of the new technology boosted steel production. They further indicate that had the BOF adoption not taken place, little output would have been achieved with the OHF: annual growth of merely 2.3 percent, far below the actual 15.2 percent growth achieved in the study period (1957 – 1968). This is due to our previous finding that the BOF produces more steel than does the OHF given the same amount of inputs (capital size in particular), and that the capital efficiency of the BOF is far greater than the loss of experience upon the adoption of BOF.

Although we cannot assess such a hypothetical question as what would have happened to steel output had the MITI not negotiated a lower license fee on behalf of all steel makers, it appears that MITI intervention did help lower a barrier to Japanese firms accessing the new technology. As a consequence, steel production quadrupled over the decade to raise Japan to the status of the world's largest steel exporter toward the end of our sample period.

6 Conclusion

This paper investigated the effects on productivity of new technology adoption, using plant-level data pertaining to the Japanese steel industry. In the 1950s and 1960s, the steel industry experienced a rapid diffusion of BOF technology, which was praised as "unquestionably one of the greatest technological breakthroughs in the steel industry during the twentieth century" (Hogan, 1971: 1543). It is known that furnace operation required vintage-specific learning by doing. Estimation of the production function indeed found a significant learning effect, comparable to the level found in other studies of learning by doing. The large learning effect associated with the old technology (i.e., OHF) implies that productivity falls after the adoption of the new technology (i.e., BOF). We indeed identified a substantial productivity drop, estimated at over 14 percent, upon the BOF adoption. We also found that it would have taken more than three years to overtake the productivity level previously achieved with the OHF technology. Although striking as they seem, our results do not lie outside the range of predictions based on calibration of the models of embodied vintage-specific technological changes (surveyed in Greenwood and Jovanovic, 2001). The above results are robust to econometrics problems, including endogeneity of input choice and self-selection of technology choice, in the production function estimation.

Growth accounting, based on the estimated production function, indicates that TFP played a minor role. The small TFP estimate is mostly attributable to the loss of vintage-specific experience caused by adoption of the BOF by many plants. Traditional treatment of capital as homogenous would miss this productivity slowdown, as has already been pointed out by Gort and Wall (1998). Indeed, TFP growth more than doubles if we apply the faulty assumption of homogenous vintage capitals (Section 4 discussed the test statistics presented in Table 4 reject this assumption of homogeneousness). We find, in passing, that productive plants are likely to adopt the new technology, and that the adoption is timed to occur right after peak TFP is achieved with the old technology.

Although TFP growth was small, adoption of the BOF was of considerable help to steel production in the study period. This is because the BOF was a far more efficient technology than was the OHF, in that it produced more steel using the same amounts of inputs. If BOF adoption had not taken place, steel output would have grown at a mere 2 percent annually, in a stark contrast to the actual growth rate of 15 percent.

Despite the large loss of OHF-specific experience, the steel industry kept up the rapid diffusion of BOF technology. We argued that this high diffusion rate had been fueled by MITI efforts to lower the new technology license fee for Japanese use. Government negotiation with the patent holder lowered the barrier to Japanese steel makers accessing BOF technology. This government assistance encouraged BOF adoption, and as a result, steel production quadrupled during our study period. Based on the finding that the steel industry had a significant impact on GDP growth in

Japan in the 1960s (Nakamura, 1978: 235)[18], we could even associate the MITI intervention with the subsequent period of economic growth in Japan. This empirical study thus indirectly supports the theoretical implications of Parente and Prescott (2001), which claims that removal of barriers to the technology frontier enhance economic growth.

A Estimation Details on Proxy Method

This appendix describes the proxy method employed to estimate (1). The appendix closely follows the steps in the estimation recipe described in Levinsohn and Petrin (L-P, 2003). Our approach differs from that of the method in that we have two state variables (capacity size and experience), and in that we estimate a production function for each technology. Section A.1 discusses a method that controls for endogeneity in input choice, and Section A.2 adds a correction method for sample selection.

A.1 Endogeneity Issue

Major inputs for steel production are pig iron and scrap. We assume that the sum of these inputs, m_t^s, is entirely determined by the unobserved productivity, capacity, and experience of technology s at time t:

$$m_{it}^s = m^s \left(\omega_{it}^s, k_{it}^s, z_{it}^s\right). \tag{2}$$

To account for the considerable technological differences between furnace types, we define the input demand by s. More of the steel inputs are demanded with an increase in productivity shock (ω_{it}^s), capacity size (k_{it}^s), or experience level (z_{it}^s).[19] The monotonicity condition allows us to invert function (2) to obtain $\omega_{it}^s = h^s \left(m_{it}^s, k_{it}^s, z_{it}^s\right)$. We can take the inverse of (2) only for the positive values of inputs. The invertibility condition holds for the intermediate inputs, but does not hold for the use of investment in our data, since many plants reported zero investment, as presented in Table 3. Note that the function $h(\cdot)$ does not contain an error. To minimize the bias from misspecification, we allow for the proxy function to be fully flexible in the following estimation. Substituting this productivity equation into (1), we obtain:

$$y_{it}^s = x_{it}^s \beta_x^s + \phi^s \left(m_{it}^s, k_{it}^s, z_{it}^s\right) + \varepsilon_{it}^s, \tag{3}$$

[18] Nakamura (1978) finds that a one-percent increase in the physical capital of the steel industry would have induced 0.32 percent of Japanese GDP growth. The magnitude of this impact is the second largest among two-digit SIC industries, followed by construction (0.33).

[19] We found empirical support for the monotonicity property by using a series expansion of the function m_{it}^s in (3), with the obtained estimate of ω_{it}^s.

where $\phi^s(m_{it}^s, k_{it}^s, z_{it}^s) \equiv k_{it}^s\beta_k^s + z_{it}^s\beta_z^s + \tau^s + \lambda_t + h^s(m_{it}^s, k_{it}^s, z_{it}^s)$. The new production function (3) is partially linear with an unknown function, ϕ^s. The coefficients, β_k^s and β_z^s, cannot be directly recovered from (3), because the corresponding variables occur twice in ϕ^s. We estimate β_x^s in (3), using the third-order polynomial to approximate ϕ^s with a full set of interactions of the constants, m_{it}^s, k_{it}^s, and z_{it}^s. We have severe collinearity between variables with the fourth- and the higher-order polynomials, but obtained similar results. This method corrects for the endogeneity in β_x^s, because the omitted variable, ω_{it}^s, is fully recovered by the proxy function. Using the estimates of β_x^s for all s, we turn to the estimation of the other parameters. We rewrite (3) as:

$$y_{it}^s - x_{it}^s\widehat{\beta_x^s} = k_{it}^s\beta_k^s + z_{it}^s\beta_z^s + \tau^s + \lambda_t + \omega_{it}^s + \varepsilon_{it}^s, \tag{4}$$

where $\widehat{\beta_x}$ is the estimate of β_x obtained from the previous paragraph. If ω_{it}^s is not serially correlated, we can estimate (4) with the two-stage least squared method. We use as the instruments one-period lagged capital (k_{it-1}^s), experience (z_{it-1}^s), material, fuel, and labor inputs (m_{it-1}^s and x_{it-1}^s), and year and technology dummies. The current productivity shock should not affect the variables determined in the past under the assumption of uncorrelated productivity. Two statistical tests find evidence against this assumption of no serial correlation. The standard J test (i.e., the test of overidentifying restrictions) would reject the orthogonality condition between some of the instruments and the productivity shock, and the Durbin-Watson test of the existence of serial correlation would find a significant AR(1) coefficient of 0.73 with a standard error of 0.03. In view of the persistent productivity shock, we follow the procedure suggested by Olley and Pakes (1996) and L-P (2003): We assume that ω_{it}^s follows a random walk, and that the predetermined variables, k_{it}^s and z_{it}^s, are uncorrelated with noise from the shock, $\xi_{it}^s \equiv \omega_{it}^s - E(\omega_{it}^s|\omega_{it-1}^s)$. We thus obtain the following residuals:

$$\xi_{it}^s + \varepsilon_{it}^s = y_{it}^s - x_{it}^s\widehat{\beta_x^s} - k_{it}^s\beta_k^s - z_{it}^s\beta_z^s - \tau^s - \lambda_t - E(\omega_{it}^s|\omega_{it-1}^s), \tag{5}$$

where the last term in the right-hand side of (5) is the conditional expectation of ω_{it}^s given ω_{it-1}^s. We denote this function as $g(\omega_{it-1}^s)$:

$$E(\omega_{it}^s|\omega_{it-1}^s) \equiv g(\omega_{it-1}^s) = g(\phi^s - k_{it-1}^s\beta_k^s - z_{it-1}^s\beta_z^s - \tau^s - \lambda_t).$$

With the estimate of ϕ^s, we use a third-order polynomial to estimate $g(\cdot)$ for candidate values for $\beta^s \equiv (\beta_k^s, \beta_z^s, \tau^s, \lambda_t)$. We use Cobb-Douglas estimates of β^s for the initial values, and update them using the following generalized method of moment (GMM) estimation routine. The moment condition is such that a set of exogenous variables, Ξ, is orthogonal to the GMM error, ν_{it}^s, defined by the left-hand side of (5). We include nine variables in Ξ for each s: predetermined stock variables at t and $t-1$ (k_{it}^s, k_{it-1}^s, z_{it}^s, and z_{it-1}^s); the material input at $t-1$ (m_{it-1}^s); electricity, oil, and labor at time $t-1$ (x^s_{it-1}); and the constant by s. The input variables at t, m^s_{it}, and x^s_{it}, are not exogenous, in that they can quickly adjust to the current productivity shock. The moment conditions are established for each of the three furnace technologies. We estimate β^s (s = OHF, BOF, and EF) by minimizing the objective function, $(\Xi'\nu)'(\Xi'\nu)$, where ν is the vector of the GMM error, whose (i,t) element in the s-th block is v^s_{it}. This completes the proxy estimation method when we do not account for self selection on technology.

Standard errors of the estimates are calculated with a bootstrap technique. Since we estimate production function by furnace type, bootstrapping is also performed independently by furnace. The number of plants is 28 (276) with OHF, 18 (104) with BOF, and 50 (468) with EF, with the number of observations appearing in parenthesis. Note that our data are unbalanced, and that even for the same furnace technology, furnace life (i.e., the number of years which a furnace was active) differs by plant. We place equal probability on each of the plant observations in a data pool stratified by furnace type. We resample a plant using a replacement from a pool of plants grouped by furnace type. The resampling process is stopped when the number of observations equals or only just exceeds that of the original data. We repeat this resampling process 1000 times and construct a production function estimate distribution, from which we take the 2.5 and 97.5 percentile points to obtain the 95% confidence interval of the parameter.

A.2 Selection Issue regarding Technology

In the empirical implementation, the selectivity problem regarding technology choice is made apparent by taking expectations of (1) over the selected sample:

$$E\left(y^s_{it}|d_{it}\right) = x^s_{it}\beta^s_x + k^s_{it}\beta^s_k + z^s_{it}\beta^s_z + \tau^s + \lambda_t + E\left(\omega^s_{it}|d_{it}\right),$$

where the selection indicator, d_{it}, takes either BOF, OHF, EF, or exit for firm i at time t. If the selection indicator correlates with plant productivity, then the last term of the above equation is not equal to the unconditional expectation, $E\left(\omega^s_{it}\right)$. We assume that the latent variable that determines the type of technology is joint normally distributed with the production function errors. Under the normality assumption, we first run the following selection model on d_{it}:

$$\begin{aligned}
\Pr\left(d_{it} = BOF\right) &= 1 - F\left(c_3 - \varpi_{it}\gamma\right), \\
\Pr\left(d_{it} = OHF\right) &= F\left(c_3 - \varpi_{it}\gamma\right) - F\left(c_2 - \varpi_{it}\gamma\right), \\
\Pr\left(d_{it} = EF\right) &= F\left(c_2 - \varpi_{it}\gamma\right) - F\left(c_1 - \varpi_{it}\gamma\right), \\
\Pr\left(d_{it} = exit\right) &= F\left(c_1 - \varpi_{it}\gamma\right),
\end{aligned} \tag{6}$$

where F is the cumulative normal distribution. This ordered probit models the following four cases: plant i chooses BOF at time t, if the latent variable, $\varpi_{it}\gamma + \varepsilon_{it}^{s}$, crosses beyond c_3; OHF if it lies between c_2 and c_3; EF if it is between c_1 and c_2; and exits otherwise. We estimate γ and the three threshold values in the first-stage regression.

Decisions about technology adoption are inherently dynamic.[20] One should thus consider model (6) as a reduced form of such a dynamic decision-making process. We assume that each plant bases its adoption decision on its own productivity, market size, and other important plant characteristics. Thus, for key regressor ϖ_{it}, we include the following nine variables, two plant variables, and year dummies by vintage: capacity sizes of the three vintages from the previous period (i.e., k_{it-1}^{s} for all s); vintage-specific experience from the previous period (i.e., z_{it-1}^{s} for all s); strength of steel demand (for which we use one-year lagged output at plant i classified by vintage, namely, $\log\left(Z_{it}^{s} - Z_{it-1}^{s}\right)$ for all s), two plant variables (plant age; and blast furnace dummy, which takes 1 if the plant has a blast-furnace facility, and 0 otherwise), and year dummies.[21]

We include capacity size and experience of all three vintages to observe how the presence of other vintage capital and experience would have influenced the selection of a particular technology. The demand measure is also included by vintage. If a plant observed that its sale (thus production) of steel from vintage s declines, it would have stopped the operation of s furnace. Section 2 discussed that fact that plants with blast furnaces were more likely to adopt either BOF or OHF, and that such a likelihood would be captured by the blast-furnace dummy. Different year dummies are included by furnace type. The year dummies are to control for aggregate trends in the variables. They also control for the dynamics of the installation cost of each refining technology. Section 2 discussed that fact that the license fee for BOF use was uniform among all firms in a given year. The effect of the BOF license fee can thus be removed by the BOF year dummies. OHF and EF use did not, however, require license payment. Under the assumption of perfect competition in the refining technology market for OHF and EF, the dynamics of the installation cost of each technology can also be controlled for by using the OHF and EF year dummies.

This selection regression provides an estimate of the expected value of the error, $E\left(\omega_{it}^{s}|d_{it}\right)$, for each s, say $\widehat{\mu_{it}^{s}}$. Controlling for the sample selection, however, does not remove the endogeneity concern discussed in the Section 3. Under the assumption of constant plant productivity, the endogeneity is controlled for by the inclusion of the plant-fixed effect. If plant productivity varies with time, we need to rely on the proxy method described in Section A1, making minor changes to incorporate the sample selection correction. We assume that the productivity shock, ω_{it}^{s}, composes two elements: one is the shock inducing the selection on technology, and the other is the one

[20] Besley and Case (1994), for example, estimates a Markov Perfect Equilibrium for the adoption of HYV cotton.

[21] Oster (1982) uses a probit model to examine BOF diffusion in the United States. She does not consider the other furnace technologies, nor the importance of learning by doing in her work.

generating the endogeneity discussed in Section A1. Let us denote the latter shock $\widetilde{\omega_{it}^s}$. Following Section A1, we assume that this shock is a function of m_{it}^s, k_{it}^s, and z_{it}^s: that is, $\widetilde{\omega_{it}^s} = \widetilde{h^s}(m_{it}^s, k_{it}^s, z_{it}^s)$. The equation (3) thus can be rewritten as

$$y_{it}^s = x_{it}^s \beta_x^s + \widetilde{\phi^s}(m_{it}^s, k_{it}^s, z_{it}^s) + \rho \widehat{\mu_{it}^s} + \varepsilon_{it}^s, \tag{7}$$

where $\widetilde{\phi^s}(m_{it}^s, k_{it}^s, z_{it}^s) \equiv k_{it}^s \beta_k^s + z_{it}^s \beta_z^s + \tau^s + \lambda_t + \widetilde{h^s}(m_{it}^s, k_{it}^s, z_{it}^s)$. The rest of the estimation procedure is the same as discussed in Section A1, if we replace ϕ^s with $\widetilde{\phi^s}$ in (3) and add the new regressor, $\widehat{\mu_{it}^s}$, with coefficient ρ to be estimated at the first stage along with β_x^s. Under the normality assumption, the production function parameters in (7) are consistent with the proxy method.

The validity of the selection model relies on the assumptions of (i) the order of d_{it}'s, and (ii) the joint normal distribution. To check the robustness of the obtained results to the two assumptions, we re-estimate the production function, replacing the ordered probit with a multinomial logit model as a selection rule (see footnote 8 for details). The advantage of the multinomial logit model is that the distribution does not impose the ordering of d_{it} as an assumption. We also rerun a probit model with different orders of d_{it} from (6). We find that obtained results are similar to the baseline ordered probit results.

B Data Appendix

Our data set comprises annual plant-level furnace data describing 66 plants and 39 Japanese steel firms from 1956 to 1968. The output and input (except for labor and physical capital, as we describe below) data are from the Japan Steel Federation (1955-1970, a). The data cover approximately 90 percent of the total steel production throughout the study period. Of the various types of crude steel, we focused on ingots for rolled steel. This type of crude steel was widely used for various industries, ranging from automobile production to construction and shipbuilding. For the inputs, we collected data concerning the amounts of oil and electricity. The output and input data identify three furnace types (OHF, BOF, and EF) for each plant. More than 80 percent of the plants covered in the data operated more than one furnace of a given year. The input and output data are aggregated over these multiple furnaces of the same vintage within a plant. The results presented in Table 5 may justify this assumption, in that an explicit consideration of the existence of multiple furnaces of the same vintage capital does not significantly alter the production function estimates. The cumulative plant output by vintage is calculated starting from 1947. This assumption is reasonable, as Figure 1 indicates the devastation state of the industry that year, due to the aftermath of bombardment.

Data concerning labor input are constructed from two data sets: the number of workers at the plant level (from Japan Steel Federation, 1955-1970: a), and actual work hours averaged over workers at the firm level (from Steel Newspaper, 1955-1970). The data concerning the number of workers are not disaggregated by furnace, unlike the other input data obtained from the same source. The labor input used for the estimation is total man hours, constructed from the number of plant-level workers multiplied by the actual work hours averaged over workers at the firm level. The data thus do not distinguish between non-production workers, skilled and unskilled production workers.

The data concerning furnace capacity by plant came from companies' semiannual financial reports, which identify all furnace capacities for the 66 plants covered in our data. The data recorded capacity as of the end of year t, and investment was made only when a new furnace was built. The capacity of furnace j_s whose technology is s, of plant i at t changes as follows: $k_{it}^{j_s} = (1-\delta)\, k_{it-1}^{j_s}$, where δ is the depreciation rate. We set δ to 5 percent, to take into account that furnace efficiency may have been declining over time. The assumption of zero depreciation rate generates similar results. To be consistent with the inputs data described above, we aggregated $k_{it}^{j_s}$ over s to obtain the capital variable of furnace s of plant i at year t.

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TABLE 1

Number of Plants and Share of Output by Furnace
Classified by Firm Size, 1956 - 1968

	TOP 6 FIRMS							THE OTHER FIRMS							INDUSTRY TOTAL	
	OHF		BOF		EF		Total	OHF		BOF		EF		Total		
	total output (% tons)	plant (no)	total output (% tons)	plant (no)	total output (% tons)	plant (no)	plant (no)	total output (% tons)	plant (no)	total output (% tons)	plant (no)	total output (% tons)	plant (no)	plant (no)	firms (no)	output (M tons)
1956	72.2	15	4.5	3	1.5	9	18	15.0	11	0	0	6.8	35	39	36	9.98
1957	71.4	15	4.1	2	1.7	8	17	15.7	12	0	0	7.1	35	39	36	11.05
1958	69.8	15	7.8	2	1.5	8	17	14.0	11	0	0	6.9	33	37	36	10.63
1959	67.3	15	8.3	2	1.5	8	17	14.6	12	0	0	8.3	34	37	35	14.55
1960	61.9	15	13.5	4	1.8	9	19	13.6	13	0.2	1	8.9	36	40	37	19.17
1961	54.9	14	20.9	7	2.4	10	19	11.9	13	1.1	1	8.8	35	39	36	24.37
1962	43.7	14	34.4	8	1.9	11	19	9.9	13	1.4	1	8.7	38	42	36	23.57
1963	32.8	12	44.1	10	2.1	10	18	10.0	13	1.2	1	9.8	39	43	36	26.56
1964	29.3	12	49.8	10	2.0	12	18	8.3	13	1.7	3	8.8	38	42	35	34.11
1965	20.0	14	58.7	13	2.1	12	21	5.5	12	5.1	3	8.6	36	41	34	35.39
1966	13.4	11	65.1	14	1.7	11	21	4.5	10	7.1	4	8.1	34	38	34	41.32
1967	10.9	11	72.7	16	1.7	12	23	3.3	8	3.9	3	7.4	32	37	33	54.39
1968	4.5	9	79.6	17	1.7	12	24	3.0	7	3.8	2	7.5	32	37	33	58.89

NOTE:
The data cover 90% of the market at any given year. "TOP 6 FIRMS" are chosen in terms of market share of crude steel production. They are Yawata, Fuji, Nihon Kokan, Kawasaki, Sumitomo, and Kobe.

TABLE 2

Summary Statistics of Explanatory Variables by Furnace Types
Annual Plant Level Data from the Japanese Steel Industry, 1956 - 1968

	Unit	Mean	Std. Error	Min	Max
Open Hearth Furnace (OHF)					
Output Production	1000 tons	228.14	0.0036	0.24	3746.19
Material Inputs (pig iron + scrap)	1000 tons	274.22	0.0031	6.24	4293.36
Physical Capacity	tons	90.31	3.40	3.75	1206.74
Furnace Age	yesrs	19.22	9.61	0	50.50
Electricity	1000 kWh	6.72	0.005	0	113.53
Oil	M liters	15.05	0.006	0	170.68
Cumulative outputs by furnace/plant	1000 tons	1550.38	0.01	0.001	43322
Number of Furnaces per plant	-	4.43	4.26	1.00	28.00
Blast Furnace Dummy		0.49	0.50	0	1.00
Plant Age	years	33.65	17.27	0	67.00
Number of observations = 304					
Basic Oxygen Furnace (BOF)					
Output Production	1000 tons	964.96	0.0032	10.20	7622.23
Material Inputs (pig iron + scrap)	1000 tons	1043.65	0.0032	11.83	8281.63
Physical Capacity	tons	149.76	2.07	39.81	550.45
Furnace Age	yesrs	2.90	2.22	0	8.67
Electricity	1000 kWh	14.51	0.003	0.24	208.53
Cumulative outputs by furnace/plant	1000 tons	293.97	0.16	0	34712
Number of Furnaces per plant	-	2.81	1.43	2.00	8.00
Blast Furnace Dummy		0.98	0.16	0	1.00
Plant Age	years	31.76	20.79	0	67.00
Number of observations = 122					
Electric Furnace (EF)					
Output Production	1000 tons	36.98	0.0030	0.28	544.79
Material Inputs (pig iron + scrap)	1000 tons	37.69	0.0060	0	582.01
Physical Capacity	tons	23.23	2.54	2.34	206.69
Furnace Age	yesrs	12.86	7.05	0	27.80
Electricity	1000 kWh	32.60	0.003	0	345.45
Cumulative outputs by furnace/plant	1000 tons	135.87	0.009	0	2233
Number of Furnaces per plant	-	3.44	1.71	1.00	9.00
Blast Furnace Dummy		0.12	0.32	0	1.00
Plant Age	years	28.53	16.34	0	67.00
Number of observations = 518					
Plant-level variable					
Total Man hours	hours	89376.9	107130	808	639948

TABLE 3

Percentage of Non-zero Observations

	Investment Δ(Capacity)	Material Inputs (pig iron + scrap)	Electricity	Oil
Open Hearth Furnace	0.23	1.00	0.98	0.98
Basic Oxygen Furnace	0.21	1.00	1.00	0.44
Electric Furnace	0.24	0.99	1.00	0.54

TABLE 4

Estimation Results on Production Function (1)

	OLS		FE		Proxy Method		Proxy with Knowledge Spillover		Proxy with Selection	
	(A)		(B)		(C)		(D)		(E)	
	Est.	Std. error	Est.	Std. error	Est.	Std. error	Est.	Std. error	Est.	Std. error
Labor	0.045	0.031	0.314 [a]	0.060	0.020	0.054	0.020	0.054	0.107	0.074
Electricity^{OHF}	0.054 [b]	0.024	0.087 [a]	0.021	-0.007	0.016	-0.007	0.015	-0.001	0.015
Electricity^{BOF}	0.078	0.065	0.082	0.063	0.010	0.022	0.010	0.021	0.011	0.032
Electricity^{EF}	0.252 [a]	0.037	0.143 [a]	0.034	-0.008	0.196	-0.008	0.194	-0.017	0.201
Oil^{OHF}	0.117 [a]	0.022	0.086 [a]	0.020	0.023	0.075	0.023	0.068	0.022	0.072
$\text{Capital size}^{OHF}$	0.389 [a]	0.035	0.339 [a]	0.040	0.403 [a]	0.072	0.407 [a]	0.074	0.431 [a]	0.072
$\text{Capital size}^{BOF}$	0.730 [a]	0.084	0.653 [a]	0.094	0.818 [a]	0.127	0.848 [a]	0.121	0.794 [a]	0.137
Capital size^{EF}	0.505 [a]	0.037	0.526 [a]	0.042	0.578 [a]	0.175	0.578 [a]	0.168	0.583 [a]	0.168
Experience^{OHF}	0.429 [a]	0.038	0.394 [a]	0.037	0.458 [a]	0.121	0.466 [a]	0.126	0.439 [a]	0.132
Experience^{BOF}	0.197 [a]	0.039	0.227 [a]	0.034	0.212 [a]	0.042	0.194 [a]	0.042	0.199 [a]	0.052
Experience^{EF}	0.280 [a]	0.025	0.217 [a]	0.026	0.330 [a]	0.126	0.342 [b]	0.144	0.313 [b]	0.129
$\text{Other\_Experience}^{OHF}$	-		-		-		-0.005	0.010	-	
$\text{Other\_Experience}^{BOF}$	-		-		-		0.014	0.008	-	
$\text{Other\_Experience}^{EF}$	-		-		-		-0.022	0.017	-	
$\text{Select. Bias Correct.}^{OHF}$	-		-		-		-		0.084	0.075
$\text{Select. Bias Correct.}^{BOF}$	-		-		-		-		0.072	0.091
$\text{Select. Bias Correct.}^{EF}$	-		-		-		-		0.166	0.133
Chi-squared tests on OHF=BOF=EF	72.72 [a]		87.07 [a]		15.59 [b]		21.30 [b]		11.85	
Learning Rate for OHF	34.6		31.4		37.4		38.1		35.6	
Learning Rate for BOF	14.6		17.0		15.8		14.4		14.8	
Learning Rate for EF	21.4		16.2		25.7		26.8		24.2	
Adj R^2 for (A) and (B)	0.998		0.88		-		-		-	
J-Statistics for (C) - (E)	-		-		1.48		1.60		1.31	

Number of Observation = 836

a Significance at the 99-percent confidence level.
b Significance at the 95-percent confidence level.

Note:
The technology and year dummy variables are included in the estimation, but their estimated coefficients are not reported in the table.
The FE specification adds plant fixed effect to the OLS.

TABLE 5

Estimation Results on Production Function (1) with Number of Furnaces

	Proxy Method (F)		Proxy Method with Technology Selection (G)	
	Est.	Std. error	Est.	Std. error
Labor	0.020	0.054	0.107	0.075
Electricity^{OHF}	-0.007	0.016	-0.001	0.016
Electricity^{BOF}	0.010	0.022	0.011	0.031
Electricity^{EF}	-0.008	0.204	-0.017	0.197
Oil^{OHF}	0.023	0.072	0.022	0.071
Capital size (No. Furnace≤2)^{OHF}	0.383 [a]	0.145	0.408 [a]	0.153
Capital size (No. Furnace>2)^{OHF}	0.355 [a]	0.084	0.387 [a]	0.080
Capital size (No. Furnace≤2)^{BOF}	1.116 [a]	0.280	1.100 [a]	0.341
Capital size (No. Furnace>2)^{BOF}	0.926 [a]	0.296	0.989 [a]	0.340
Capital size (No. Furnace≤2)^{EF}	0.809 [a]	0.233	0.793 [a]	0.225
Capital size (No. Furnace>2)^{EF}	0.399 [b]	0.184	0.440 [b]	0.187
Experience (No. Furnace≤2)^{OHF}	0.449 [a]	0.104	0.433 [a]	0.116
Experience (No. Furnace>2)^{OHF}	0.469 [a]	0.117	0.449 [a]	0.129
Experience (No. Furnace≤2)^{BOF}	0.287 [a]	0.083	0.279 [a]	0.104
Experience (No. Furnace>2)^{BOF}	0.322 [a]	0.097	0.284 [b]	0.144
Experience (No. Furnace≤2)^{EF}	0.307 [b]	0.136	0.297 [b]	0.130
Experience (No. Furnace>2)^{EF}	0.392 [a]	0.145	0.363 [b]	0.144
Select. Bias Correct.^{OHF}			0.084	0.072
Select. Bias Correct.^{BOF}			0.072	0.083
Select. Bias Correct.^{EF}			0.166	0.133
Returns to scale in OHF capital	-0.03	0.17	-0.02	0.18
Returns to scale in BOF capital	-0.19	0.25	-0.11	0.30
Returns to scale in EF capital	-0.41	0.23	-0.35	0.24
Returns to scale in OHF experience	0.02	0.05	0.02	0.05
Returns to scale in BOF experience	0.03	0.09	0.01	0.11
Returns to scale in EF experience	0.09	0.06	0.07	0.07
J-Statistics	1.26		1.63	

Number of Observation = 836

a Significance at the 99-percent confidence level.
b Significance at the 95-percent confidence level.

Note:
The technology and year dummy variables are included in the estimation, but their estimated coefficients are not reported in the table.

TABLE 6

Model Predictions

	Estimated							Actual						
		Largest Furnaces Shares (%)			Smallest Furnaces Shares (%)				Largest Furnaces Shares (%)			Smallest Furnaces Shares (%)		
	Industry Output (M tons)	OHF Yawata (Yawata)	BOF Yawata (Yawata)	EF Yawata (Yawata)	OHF Topy (Tokyo)	BOF Osaka (Nishijima)	EF Tohoku Specialty Steel	Industry Output (M tons)	OHF Yawata (Yawata)	BOF Yawata (Yawata)	EF Yawata (Yawata)	OHF Topy (Tokyo)	BOF Osaka (Nishijima)	EF Tohoku Specialty Steel
1957	10.19	23.11	-	0.50	1.08	-	0.04	11.23	24.60	-	0.40	1.00	-	0.07
1958	10.40	21.58	4.11	0.39	0.95	-	0.05	10.49	22.89	4.03	0.29	0.90	-	0.08
1959	14.91	21.64	5.16	0.37	0.87	-	0.04	14.27	22.59	5.06	0.31	0.84	-	0.07
1960	19.22	17.96	9.30	0.34	0.75	-	0.04	18.73	18.10	8.38	0.34	0.71	-	0.15
1961	23.38	15.77	11.08	0.34	0.70	-	0.04	23.80	15.74	9.85	0.25	0.67	-	0.06
1962	22.24	13.15	13.99	0.29	0.47	-	0.05	23.55	11.59	12.43	0.20	0.42	-	0.06
1963	25.59	10.27	14.80	0.28	0.35	-	0.04	26.10	9.01	13.92	0.21	0.33	-	0.05
1964	32.03	8.85	14.84	0.27	0.38	-	0.04	33.55	7.89	14.61	0.22	0.39	-	0.05
1965	31.41	7.09	14.90	0.26	0.40	0.87	0.03	34.02	6.12	14.60	0.25	0.41	0.83	0.03
1966	40.57	4.97	13.93	0.25	0.35	0.79	0.03	40.18	4.21	13.87	0.21	0.37	0.82	0.04
1967	51.79	3.72	14.61	0.25	0.30	0.70	0.03	52.71	2.97	14.39	0.21	0.31	0.70	0.03
1968	57.71	1.74	13.28	0.23	0.23	0.59	0.03	57.86	1.41	13.17	0.19	0.25	0.62	0.03

Notes:
For each entry of furnace production share, we list a company name in the first row, and a plant name in the second row inside the parenthesis,
Tohoku Specialty Steel owned only one plant. Yawata adopted the BOF in 1958, and Osaka (Nishijima plant) did so in 1965.
To calculate the predicted values, we use the estimates (C) in Table 4.

TABLE 7

Various Measures on TFP Growth (%), 1957-1968

	No. BOF Adopting	Conventional TFP Growth			Vintage-Capital TFP Growth			Output Growth
		OLS	FE	Proxy	OLS	FE	Proxy	(From Figure 1)
1957-58	2	0.64	2.25	-3.48	-5.98	-6.52	2.41	-6.55
1958-59	0	18.04	15.17	25.37	19.15	15.69	29.53	35.97
1959-60	0	14.83	14.29	13.05	12.16	10.81	10.07	31.31
1960-61	2	17.59	15.07	16.46	14.06	11.32	-6.06	27.02
1961-62	3	3.86	6.34	-1.48	-22.47	-18.37	-34.93	-1.01
1962-63	1	14.27	12.24	12.90	-6.69	-2.64	-11.04	10.82
1963-64	2	29.69	28.48	22.04	24.14	24.06	5.12	28.51
1964-65	1	9.50	8.93	5.09	-4.92	-0.41	-20.69	1.41
1965-66	2	24.61	22.21	32.94	15.77	19.14	8.97	18.10
1966-67	0	20.23	19.81	17.83	15.00	14.08	5.37	31.20
1967-68	0	13.95	12.43	7.58	9.65	12.78	-1.03	9.77
Average (%)		15.20	14.29	13.48	6.35	7.27	-1.12	16.96

Note:
The estimated TFP in the table is share-weighted average of the plant level productivity measure, using furnace/plant-level output share as weight. Conventional TFP is calculated by estimating (1) without the subscript s (i.e., ignoring the difference in furnace vintage). Vintage-Capital TFP is calculated by using the estimates of OLS (A), FE (B), and proxy (C) methods presented in Table 4.

TABLE 8

Sources of Productivity by furnace type

Average annual share-weighted TFP components

	OHF			BOF			EF		
	Contributions of			Contributions of			Contributions of		
	Learning by Doing	Disembodied Technical Progress	Inputs (Use of OHF inputs)	Learning by Doing	Disembodied Technical Progress	Inputs (Use of OHF inputs)	Learning by Doing	Disembodied Technical Progress	Inputs (Use of OHF inputs)
1957	6.85	3.79	2.48	-	6.48	4.56	3.87	4.49	3.15
1958	6.94	3.71	2.47	2.73	6.18	4.55	3.91	4.44	3.14
1959	7.00	3.95	2.53	2.93	6.06	4.66	3.98	4.68	3.22
1960	7.04	4.05	2.56	3.03	6.43	4.71	4.01	4.78	3.25
1961	7.11	4.04	2.54	2.90	6.73	4.67	4.08	4.87	3.23
1962	7.18	3.76	2.51	2.96	6.41	4.63	4.12	4.72	3.19
1963	7.21	3.66	2.49	3.10	6.44	4.58	3.99	5.01	3.16
1964	7.27	3.71	2.46	3.16	6.56	4.53	4.21	4.76	3.12
1965	7.33	3.40	2.45	3.22	6.49	4.51	4.31	4.70	3.11
1966	7.35	3.41	2.45	3.25	6.64	4.50	4.39	4.88	3.10
1967	7.35	3.53	2.40	3.32	6.64	4.39	4.45	4.94	3.03
1968	7.22	3.32	2.37	3.38	6.66	4.33	4.50	4.93	2.99

Note:
The productivity measure in the table is in logarithm. Disembodied Technical Progress is the sum of the estimates of ω and furnace- and year-specific components. The estimates of (C) from Table 4 are used. The TFP is share-weighted average of the plant level productivity measure, using furnace/plant-level output share as weight.
Since z is the histrical cumulative output, and the first BOF was installed in 1957, no learning constribution is recorded for the year.
To construct contributions of inputs, we set the inputs of different furnaces to be the same as the OHF inputs for each year. Thus th measure of input contributions is the mean value of $x^{OHF}\beta_x^s+k_{OHF}\beta_k^s$ for s = either OHF, BOF, or EF.

TABLE 9

Plant-level TFP
Grouped by Furnace Technology Types

	Non-upgrading Plants									Upgrading Plants					
	OHF only (A9)		OHF & EF (B9)		EF only (C9)		BOF only (D9)		Share-weighted mean (E9)	OHF →BOF (F9)		OHF →EF (G9)		Share-weighted mean (H9)	Ratio Exp(H9 - E9) (I9)
	TFP	Share (%)	TFP	Share (%)	TFP	Share (%)	TFP	Share (%)	TFP	TFP	Share (%)	TFP	Share (%)	TFP	
1957	10.19	6.94	10.10	7.59	8.37	5.94	-	-	9.63	10.70	76.22	9.17	3.31	10.64	2.74
1958	9.94	5.28	9.95	6.64	8.36	5.11	-	-	9.47	10.58	79.85	9.04	3.13	10.52	2.86
1959	10.35	5.66	10.23	6.36	8.69	5.90	-	-	9.76	10.84	79.56	9.06	2.52	10.78	2.77
1960	10.46	5.03	10.28	6.03	8.87	6.44	-	-	9.81	10.93	80.25	9.04	2.26	10.88	2.91
1961	10.44	5.08	10.14	5.01	9.00	6.16	9.50	3.66	9.75	10.90	77.62	9.28	2.47	10.85	3.01
1962	9.84	2.31	9.96	4.44	8.87	5.98	9.32	4.59	9.40	10.40	80.65	9.16	2.02	10.37	2.64
1963	9.92	2.05	9.97	4.50	9.08	7.53	9.63	5.20	9.53	10.24	78.73	9.24	1.99	10.22	2.00
1964	9.99	2.00	10.01	3.61	9.02	6.47	9.97	5.46	9.63	10.26	80.75	9.18	1.71	10.24	1.84
1965	9.39	1.72	10.05	3.78	9.06	6.21	9.61	9.30	9.51	10.01	77.26	9.18	1.72	9.99	1.63
1966	9.48	1.49	9.91	3.27	9.34	5.91	9.67	13.51	9.61	10.10	74.46	9.37	1.35	10.09	1.61
1967	9.54	1.32	9.98	2.83	9.46	5.19	9.60	17.34	9.61	10.19	72.22	9.34	1.09	10.18	1.76
1968	9.50	1.18	9.96	2.59	9.49	4.97	9.76	25.38	9.72	10.18	64.73	9.58	1.15	10.17	1.56
No. Plants	5		5		33		5		48	13		5		18	

Note:

The productivity is obtained by averaging over furnace/plant-level productivity, weighing by output share. The productivity measure in the table is in logarithm.

FIGURE 1
Steel Production in Japan
1931-1969

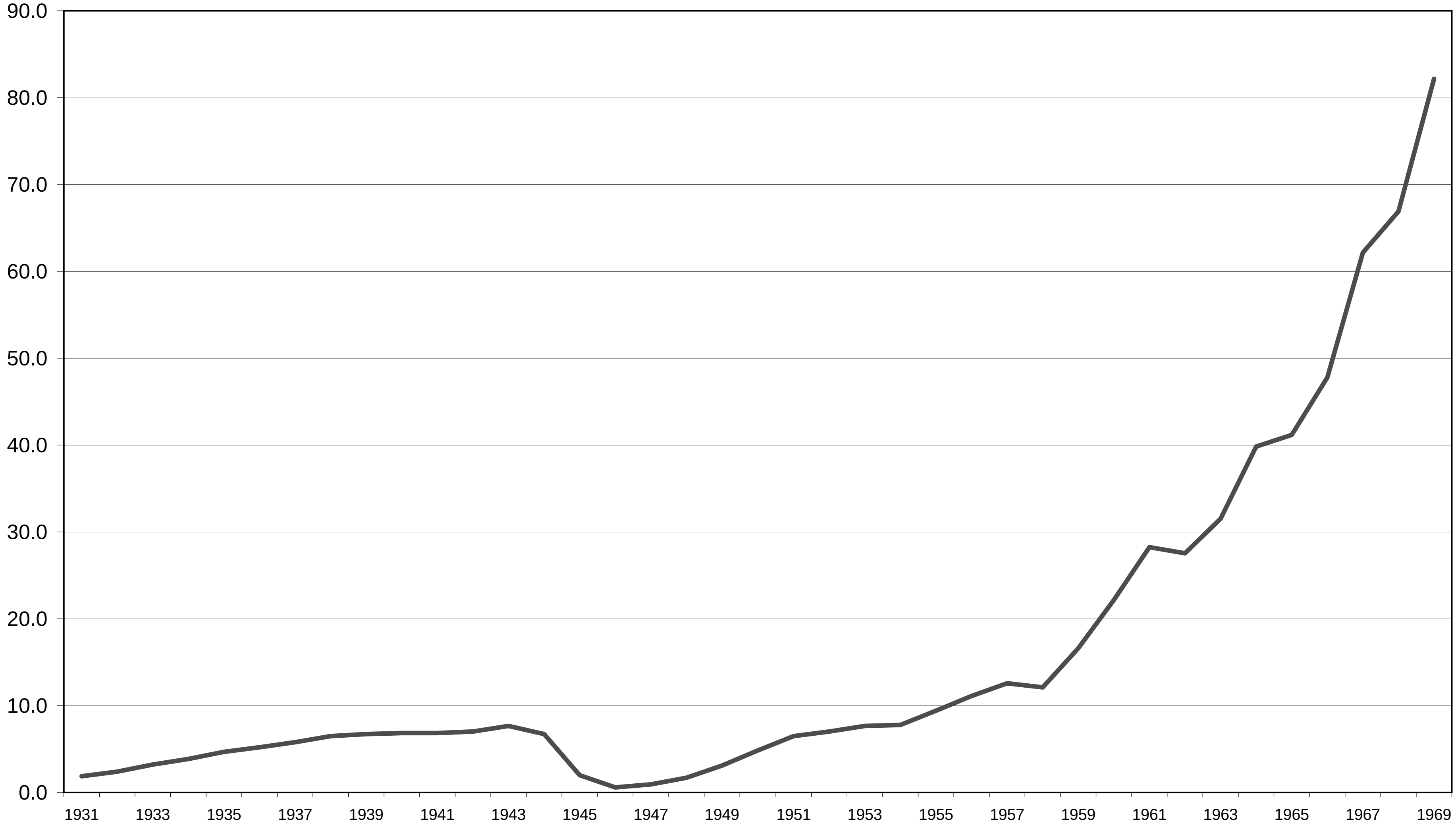

FIGURE 2

TFP Changes for the BOF Adopting Plants
Based on the Estimates from Table 3

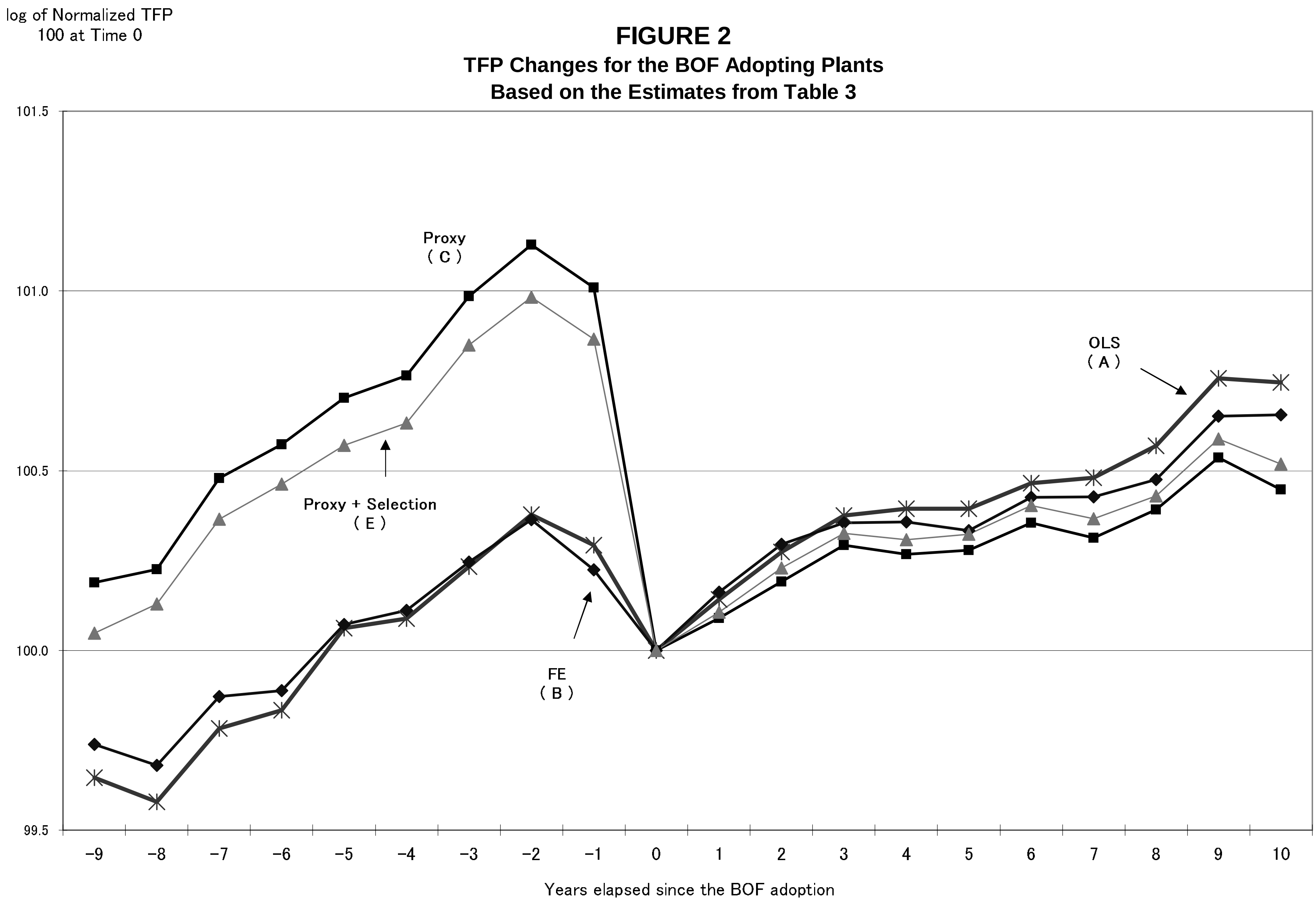

FIGURE 3
Industry-level Outputs and TFP, 1957 - 1968
(Based on estimates (C) in Table 4)