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Productivity, Capital Utilization, and Intra-firm Diffusion: A Study of Steel Refining Furnaces

Tsuyoshi Nakamura
Tokyo Keizai University

Hiroshi Ohashi
University of Tokyo

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Tsuyoshi Nakamura †   Hiroshi Ohashi ‡

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Abstract

This paper examines the intra-firm diffusion of new technology in the Japanese steel industry. The introduction of the basic oxygen furnace was the greatest breakthrough in steel refining in the last century. Using unique panel data concerning capital utilization, the paper estimates total factor productivity by technology type, and associates the estimate with intra-firm diffusion. Estimation results reveal that the productivity difference between the old and new technologies plays an important role. The paper also finds that in operation, the old technology can better respond to changes in market demand, which brings about counter-cyclicality in the measured productivity.

JEL: D24, L61, O14, O33.

Keywords: intra-firm diffusion; innovation; technological change; TFP

1 Introduction

Diffusion of new technology has been viewed as a main driving force of economic growth. An important set of questions often raised in the literature concerns what factors determine a firm's decision to adopt a new technology. While this issue of inter-firm technology diffusion has been extensively studied, the adoption of new technology is not in and of itself sufficient for economic growth. For the social benefits of innovation to be realized, the outcome of an innovation must not only be adopted by a firm, but also be extensively utilized in economic activities. Productivity and outputs would not rise quickly in response to the adoption of new technology, if the utilization of

the technology remains low. As Mansfield (1963: 356) explains, the accurate measurement of the rate of intra-firm diffusion—the rate at which a particular firm substitutes a new technology for old in its production process—requires firm-level data that identify capital utilization by vintage. Existing research, however, has measured intra-firm diffusion by the proportion of a firm's capital in *place*, not in *use*, that incorporates the new technology. Using unique plant-level panel data that identify utilization by technology type, we seek to shed new light on the study of intra-firm diffusion.[1]

Using data pertaining to the Japanese steel industry, this paper analyzes two aspects of intra-firm diffusion that have received little previous empirical examination. These aspects are: (1) the role of old technology in responding to demand shocks; and (2) the relationship between firm size and productivity differences between old and new technologies. These aspects of intra-firm diffusion could not be examined without the data that describe capital in use by technology type. As the object of study we chose refining furnace technology in the Japanese steel industry. In the 1950s and 1960s, many integrated steel makers updated their technology, shifting from the conventional open-hearth furnace (OHF) to the imported basic oxygen furnace (BOF). The introduction of the BOF was praised as being "unquestionably one of the greatest technological breakthroughs in the steel industry during the twentieth century" (Hogan, 1971: 1543). Interestingly, the period of the rapid dissemination of BOF technology coincides with that of the remarkable growth Japan experienced in the wake of the devastation wreaked by World War II. In particular, the steel industry expanded its production more than fourfold between 1953 and 1964, raising Japan to the status of the world's largest steel exporter in 1969. As we discuss in Section 2, intra-firm diffusion played a major role in BOF diffusion, resulting in the rapid growth of the Japanese steel industry in the 1950s and 1960s. Restricting our study to examining refining furnace technology also allows us to abstract from market structure effects in our study; virtually all steel plants faced the same market for crude steel, a homogeneous product manufactured from the refining furnaces. The nature of the market, along with the utilization data, allow our analysis to focus on the influence of other determinants of intra-firm technology diffusion, including factors (1) and (2), as we describe below.

Industry circles have recognized that producing steel involves substantial learning from and during production.[2] Given experience of repetitive tasks, steelworkers are likely to learn from cumulative experience how such tasks can be done more quickly and efficiently. It was the experience and judgment of steelworkers that made it possible for plants to adjust the frequency and the size of furnace operations when faced with volatile steel demand in the 1950s and 1960s. The

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[1] Although the data used here refer to plants rather than firms (subject to the comments on the fixed effects used in Section 4.2), we use the terms "plant" and "firm" interchangeably, so as to conform to current usage in the literature.

[2] The importance of "learning by doing" in Japanese steel production is empirically analyzed in Ohashi (2005), and Nakamura and Ohashi (2006).

practice that emerged was that the new and efficient technology (i.e., BOF) was used to provide a constant, baseline level of steel production regardless of total demand, and that the familiar but inefficient technology (i.e., OHF) was employed as needed according to the volatility of steel demand. Although this resource allocation practice is observed in other industries (such as power generation), its effect on intra-firm diffusion has not been empirically examined. Our estimates indicate that the practice has had a significant influence on the diffusion rate of the BOF. We also found that this practice brought about counter-cyclicality in measured productivity in our data, similar to the findings of Basu, Fernald, and Kimball (2004) in their analysis of 29 U.S. industries in the 1949–1996 period.

Differences in the productivity of new and old technologies across plants have been a main focus of the diffusion literature (see, for example, Mansfield, 1968; Battisti and Stoneman, 2005). If a new technology is more productive than an old one, a firm will shift its production process faster than otherwise from the old to the new technologies, so as to minimize the opportunity cost of retaining the old technology. The existing literature, however, has not yet estimated these productivity differences, instead employing plant size (in terms of the number of workers) as a proxy for such an effect. Whether plant size serves as an appropriate indicator of productivity differences remains an open question. Our panel dataset lets us estimate total factor productivity (TFP) of the OHF and BOF, respectively, and to associate the obtained productivity estimates with plant size. The paper finds that productivity differences between the two furnace technologies indeed strongly correlate with plant size, and that they play a major role in intra-firm diffusion. Furthermore, the paper provides an explanation as to why plant size serves a proxy suitable for representing the productivity differences in our application.

In his survey of the literature on new technology diffusion, Geroski (2000) identifies two leading models: the epidemic and probit models. The first model, originally proposed by Mansfield (1963), predicts that the extent of use of a new technology within a firm increases with the number of years since the first adoption. Figure 1 traces the changes in the output share produced by the BOF for each of the thirteen plants represented in our data. Although the BOF share generally increased over the study period, the epidemic model cannot explain the BOF use observed in Figure 1; the years elapsed since the first BOF adoption, with the use of a third-order polynomial, only explain twenty percent of the total variability of the BOF output share (a finding similar to that of Battisti and Stoneman, 2005). Thus we do not rely solely on the epidemic model, but also incorporate features of the alternative model—the probit model—in analyzing intra-firm diffusion in this paper. The probit model presumes that differences in the diffusion rate reflect differences in firm and technology characteristics. Estimation of the model indicates the importance of the previously described factors (1) and (2) as determinants of the intra-firm diffusion of new technology.

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The rest of the paper is organized as follows. Section 2 provides an overview of the Japanese steel market after the second World War. It describes several important features of the market that have a direct bearing on the formulation of empirical strategies and on the interpretation of quantitative results discussed in the subsequent sections. Section 3 describes a method for estimating the TFP of furnace technologies. The panel feature of our dataset enables us to correct for endogeneity problems when measuring productivity. Using the obtained productivity estimates, Section 4 presents our estimation models and results. First, Section 4.1 presents the results of survival analysis, and identifies economic determinants of the duration for which the old technology remained in use after the adoption of the BOF. This survival analysis confirms the relationship between plant size and the duration of old technology use. Section 4.2 examines what drives the pattern of intra-firm diffusion observed in Figure 1. The analysis reveals the importance of (1) the role of old technology in responding to demand shocks; and (2) the relationship between plant size and productivity differences between old and new technologies in intra-firm diffusion. We also discuss the implications for intra-firm diffusion rates of the BOF in the United States. Section 5 concludes the presentation, and is followed by two appendices: Appendix A shows a derivation of the regression model of intra-firm diffusion presented in Section 4.2, and Appendix B describes the data used in this paper.

2   Overview of the Post-war Japanese Steel Market

In the early 1950s, most Japanese steel 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 subsequently transformed into crude steel in a second furnace by removing carbon and other elements. The prevalent technology used in this second or "refining" stage was the OHF, which blows burning fuel gas over the molten pig iron: this gas provides the heat required to purify the pig iron. In the late 1950s, the OHF began rapidly losing ground to the BOF. A major advantage of the BOF was that it refined molten iron and scrap charge into steel in approximately 45 minutes—a sharp decrease from the 6 hours that the OHF normally required then.

Invented in Austria, BOF technology was further developed by Japanese steel makers after being imported to Japan. The Japanese have been responsible for developing the two most important improvements in BOF hardware: the multi-hole lance and the OG system (Lynn, 1982: 34; Odagiri and Goto, 1996: 149). The multi-hole lance reduces splashing in the BOF, thus increasing steelmaking yield and improving refractory life. Over the course of our study period, the BOF lance continuously improved its capability for softer blowing at lower velocities while achieving higher production rates. The OG system allows the recovery of gases from the BOF. It controls pollution and helps reduce energy costs, while contributing to steelmaking yield. These "user-centered tech-

nological improvements" (von Hippel, 2005) associated with the BOF are known to have contributed to the increase in steelmaking productivity in Japan. In the subsequent section, we measure the effects of these user-side technological innovations on the process of intra-firm diffusion. [3]

Figure 2 depicts the diffusion of the new technology as observed in the dataset. Three BOF diffusion paths are plotted in the figure: overall diffusion (denoted by the thin line), inter-firm diffusion (by the dotted line), and intra-firm diffusion (by the bold line). The BOF share of the industry's output rose from 0.7 in 1957 to 100 percent in 1971. This overall usage level of the new technology in the industry is attributed to changes in the number of users (inter-firm diffusion) and in the intensity of use by firms (intra-firm diffusion). The inter-firm diffusion indicates that all plants represented in the data had adopted the BOF by 1965, at which time the within-plant technology penetration had reached approximately 70 percent: then, intra-firm diffusion became the sole driving force of the overall diffusion. The figure illustrates how intra-firm diffusion is important in accounting for the penetration of the new technology, particularly in the later stages of the diffusion process. This finding has also been observed with regard to other technologies, including computer numerically controlled (CNC) machine tools as reported in Battisti and Stoneman (2004).

Industry circles have recognized that producing steel involves substantial learning from and during production. Hogan (1971) and Lynn (1982) both noted that it was only through extensive furnace use that detailed knowledge of furnace operation was gained. Both OHF and BOF refining furnaces cannot be operated without skilled workers. It was the experience and judgment of skilled workers that made it possible for plants to adjust the frequency and the size of furnace operations, while maintaining the quality and durability of the crude steel produced.

Steel demand in the 1950s and 1960s varied substantially from year to year, as shown in the last column of Table 1: the rate of steel output growth ranged from –7.3 to 42.9 percent. This volatile demand in the steel market raised the question of how to allocate production efficiently between the old and new furnaces to meet the demand. The practice that emerged was that the new and efficient technology (i.e., BOF) was used to provide a constant, baseline level of steel production regardless of total steel demand, and that the familiar but inefficient technology (i.e., OHF) was employed as needed according to the volatility of steel demand. Figure 3 illustrates, from the data, the importance of this practice. The figure plots unanticipated steel-demand shocks and detrended intra-firm OHF share. The former variable is calculated as the deviation from the AR(1) prediction of the industry-level steel demand. The figure indicates that, consistent with the practice described above, OHF production deviates upwardly from the scheduled operation level upon the arrival of unanticipated demand shocks. This practice of furnace operation is, in fact,

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[3] This paper does not consider the electric furnace (EF), because its production share was small during our study period.

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not unique to the steel industry; a similar feature is also observed in other markets, for example, the power market. In the power market, it is known that base-load power is provided by low-cost means of generation (nuclear plants, for example), higher-cost but more flexible means of generation (combustion turbines, for example) being employed to match power consumption demands. In an analogy with this power-market example, the BOF would correspond to nuclear power, and the OHF to combustion turbines.

Much theoretical and empirical research informs us that firm size plays an important role in the diffusion of new technology, and casual observation of our data indeed reveals a clear relationship between plant size and intra-firm penetration of the BOF. Figure 4 plots the year in which the first BOF was adopted (denoted by circles) and the year in which the last OHF was terminated from use (denoted by rectangles) for each steel refining plant. The adoption and termination years are sorted by plant size, as measured by the logarithmic number of workers. The figure contains two important observations. First, a negative correlation is observed between plant size and the year of new technology adoption, larger plants tending to adopt the BOF earlier. This observation, which concerns inter-firm technology diffusion, is well documented in the existing literature, as surveyed, for example, in Stoneman (2001). Second, a negative relationship is observed between plant size and the rate of intra-firm diffusion of the BOF. The figure indicates that the smallest plant needed four years to fully replace the OHF, whereas the largest plant took twelve years. The correlation between replacement speed and plant size is great enough to generate a negative correlation between plant size and the year in which the OHF ceased to be used.

While the first observation regarding inter-firm diffusion has been extensively studied, the second one has not: to address this imbalance, this paper concentrates on analyzing the second observation. Note, however, that our empirical analysis uses evidence pertaining to inter-firm diffusion. The econometric analysis described in Section 4 reports that productivity differences between furnace technologies account for the intra-firm diffusion of the BOF. The next section describes the method used to estimate the productivity of furnace technology.

3   Measuring Productivity

This section presents the method used to estimate the productivity of furnace technology, while explicitly considering differences in furnace type.[4] To do so, we require estimates of the production function, which describe the steel refining process. Considering that the two furnace technologies, OHF and BOF, exhibit considerably different operational characteristics, we allow for the pro-

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[4]The methodology described in this section is in essence similar to that used in Nakamura and Ohashi (2006). Here, however, we tailor the method to the analysis of intra-firm diffusion, instead of to the analysis of changes in plant-level productivity as was done in the earlier paper.

duction function parameters to differ in terms of technology. The description of the industry in the previous section reveals that experience was an important feature of furnace operations. The production function thus incorporates experience, as well as other control variables, such as capacity size and input measures. The productivity estimates obtained in this section are used in the diffusion analysis in Section 4.

The two vintages of furnaces both produce crude steel, a homogeneous product. Our econometric model of the production function describes how efficiently the furnaces completed the transformation process. We use the following Cobb-Douglas form with the parameters, $\beta_{X_k}^s$, β_K^s, and β_Z^s to be estimated:

$$Y_{it}^s = \prod_k (X_{kit}^s)^{\beta_{X_k}^s} (K_{it}^s)^{\beta_K^s} (Z_{it}^s)^{\beta_Z^s} \exp(u_{it}^s), \tag{1}$$

where Y_{it}^s is the annual output (in tons) for furnace s (s is either OHF or BOF) at plant i in year t. The production function comprises a number of input variables. Vector X_{it}^s includes fuels and labor along with a constant term. All furnaces use electricity as an energy source, and the OHF uses oil in addition. The k-th component of this vector is denoted by X_{kit}^s. The capacity of furnace s is indicated by K_{it}^s, and the number of years of use for furnace s is denoted by Z_{it}^s. The last variable captures two aspects of capital utilization: On one hand, this variable reflects the experience level, i.e., the extent to which extensive use of a particular furnace type leads to more efficient production. On the other, the variable also indicates the degree of capital depreciation, as furnace productivity deteriorates with age. The estimated coefficient of the variable implies which of the two effects dominates in our application.

Apart from the three factors described in (1), two important influences on steel production are plant-level efficiency of production management and improved furnace technologies. Such unmeasured determinants are represented by u_{it}^s. Productivity unobserved by the econometrician may create endogeneity in input choice.

Endogeneity in input choice arises when producers adjust the amount of material (fuels and labor in our application) according to their efficiency differences in u_{it}^s. For example, plants that are perceived to have higher productivity might use more fuels. Our response to the endogeneity problem is to use plant-, year-, and technology-specific components in the estimation. Further, we allow the technology fixed effect to differ according to the year, as follows: $u_{it}^s = \tau_i + \nu_t^s + \varepsilon_{it}^s$, where ε_{it}^s is a mean-zero error. The plant fixed component, τ_i, deals with efficiency differences between plants, differences that do not change over time. The inclusion of ν_t^s serves to control for the differences in furnace technologies, which change according to the year. It may appear to be restrictive to assume that the plant fixed component remains constant over time. However, this assumption is not unreasonable given our data, and is consistent with the observation that,

conditional on the furnace type s, the order of the plant-level production share remained constant over the sampling period. [5], [6]

The estimation result is found in Table 2. The upper part of the table presents estimates of the regression coefficients. Our inference is based on heteroskedasticity-robust standard errors. The measure of adjusted R^2 is quite high, indicating that the model fits the data well. The results of the Chi-square test presented in the table would reject the hypothesis of homogenous technology between the two furnace types, and thus justify our specification that allows for coefficients to differ according to furnace vintage.

The table shows that the input coefficients are estimated to be positive and mostly statistically significantly different from zero. 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 constant returns to scale across multiple furnaces of the same technology at the plant level. We previously investigated this issue (Nakamura and Ohashi, 2006) and determined that the finding of returns to scale is robust to this concern. The number of years of furnace use is found to be significantly positive, indicating that the effect of learning dominates that of capital depreciation in furnace technology.

Figure 5 presents estimated average TFP values for the OHF and BOF technologies, ν_t^s, where s represents either OHF or BOF, over the 1957–1968 study period. The TFP estimates in the figure confirm that the BOF (indicated by the thin line) was more efficient than the OHF (the dotted line). The figure also indicates that the TFP measures of the two technologies diverged over time: the productivity of the BOF increasing by approximately 25 percent over the study period, while the productivity of the OHF decreased by half. The productivity increase of the BOF could be due to user-centered innovations (von Hippel, 2005), including the multi-hole lance and the OG system mentioned earlier in this section. It could also be due to a feature of inter-firm diffusion process: As experience in the use of the BOF accumulated in adopting firms, some, if not all, of this experience would spread among non-adopting firms by word-of-mouth or knowledge spillover. In either case, the late adopters would benefit from knowledge transferred from other earlier adopting firms, and thus enjoy higher initial productivity when adopting the BOF. The productivity decline

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[5] The stability of market share has often been observed in other industries in Japan; see Sutton (2005) for a detailed examination of this matter.

[6] An alternative method to control for unobserved productivity is to create a proxy for u_{it}^s by introducing an input demand equation from outside the production function framework. A previous version of the present study, Nakamura and Ohashi (2006), reported that the infrequency of investment fails to use the Olley and Pakes (1996) method, and that the use of material input (pig iron and scrap in our case), as per the idea adopted from Levinsohn and Petrin (2003), generates unreasonable productivity estimates. The Levinsohn–Petrin approach has also been recently criticized by Ackerberg, Caves, and Frazer (2005). Based on these findings from Nakamura and Ohashi (2006), the present study does not employ these methods to control for unobserved productivity.

of the old furnace, on the other hand, may be primarily attributed to capital depreciation: smaller plants spent less time and effort maintaining and repairing the OHF prior to adopting the BOF. [7] Although the knowledge spillover also possibly affected OHF operation, the figure appears to indicate that the depreciation effect dominates.

While identifying the sources of furnace productivity requires further data collection, the measured productivity presented here implies a negative relationship between plant size and the rate of intra-firm diffusion. Because the early generation of the BOF exhibits lower productivity than later generations do, it takes more years for early BOF adopters to replace the old technology. One may thus wonder why larger firms adopted the new technology earlier; however, we leave this matter to the literature on inter-plant diffusion.[8]

Instead, we concentrate our analysis on intra-firm diffusion, and, in the next section, statistically analyze the role of the measured productivity differences.

4   Econometric Analysis of Intra-firm Diffusion

In this section, we statistically analyze the intra-firm diffusion of the new refining furnace technology in the post-war Japanese steel market. For this purpose, we use plant-level panel data that identify technology use by vintage. We use two empirical approaches to examine the features of the intra-firm diffusion of the BOF. The first approach is based on a hazard-rate model. Figure 4 indicated a negative correlation between plant size and the year in which the OHF ceased to be used. The proportional hazard model, which accounts for the nature of discrete time in our data, examines the robustness of this correlation.

Though useful for understanding the usage duration of the old technology, the hazard-rate approach does not help us uncover information regarding the rate of intra-firm diffusion of the new technology. We thus employ the second approach and explain the variation in the relative shares of outputs produced by the old and new technologies.

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[7]Data regarding furnace maintenance time and frequency are available for only one plant in Yawata, then the largest steel maker in Japan. We observed the four OHFs owned by the plant, and noted that maintenance time and the OHF sizes were clearly negatively correlated. Since smaller plants tend to own lower capacity OHFs, this observation is in line with our finding regarding changes in measured OHF productivity.

[8]Firm size is a commonly explored variable in the analysis of inter-firm diffusion. Many studies in the literature reported a positive correlation between firm size and adoption speed. However, as Geroski (2000: 612) pointed out, different interpretations of what firm size might mean are not always mutually consistent, and thus it is hard to unambiguously interpret the empirical results.

4.1 Duration Analysis of New Technology

This section examines the robustness of our observation regarding Figure 4, concerning the relationship between plant size and the number of years a plant took to replace the old with the new technologies. Because our data only allow us to infer the timing of the plant's technology adoption and retirement decisions using yearly intervals, we use the discrete-time version of the proportional hazard model. We will briefly describe our estimation method, which follows that of Prentice and Gloeckler (1978). Let T_i be the length of the spell for plant i. The hazard for plant i at time t is defined by,

$$\lambda_i(t) \equiv \lim_{\rho \to 0} \frac{\Pr[t + \rho > T_i \geq t]}{\rho}.$$

The hazard here is parameterized using a proportional hazard form: $\lambda_i(t) = \lambda_0(t) \exp(w_i(t)' \beta)$, where $\lambda_0(t)$ is the baseline hazard at time t, w is a vector of covariates, and β is a vector of unknown parameters. We assume that the plant, not the firm, is the decision unit concerning when to stop using the old furnace technology. [9] Our observations are grouped into yearly intervals, $A_\tau = [a_{\tau-1}, a_\tau)$, $\tau = 1, ..., r$ with $a_0 = 0$ and $a_r = \infty$. Note that the difference between $a_{\tau-1}$ and a_τ is one. The vector of covariates is allowed to be time dependent, but fixed within the year interval. The probability of the spell lasting until the τ-th year, provided that it lasts until the $(\tau - 1)$-th year, is given by:

$$
\begin{aligned}
\Pr[T_i \geq a_\tau | T_i \geq a_{\tau-1}] &= \exp\left[-\int_{a_{\tau-1}}^{a_\tau} \lambda_i(u)\, du\right] \\
&= \exp\left[-\exp\left(w_i(\tau)' \beta + \gamma(\tau)\right)\right],
\end{aligned}
$$

where $\gamma(\tau) = \ln\left(\int_{a_{\tau-1}}^{a_\tau} \lambda_0(u)\, du\right)$. We assume that the baseline hazard, $\lambda_0(t)$, is constant. [10] We obtain estimates of β and γ_0 by maximizing the following likelihood function using the number of observations, N:

$$
\prod_{i=1}^{N} \left[\left\{ 1 - \exp\left[-\exp\left(w_i(R_i)' \beta + \gamma_0\right)\right] \right\} \prod_{\tau=1}^{R_i - 1} \exp\left[-\exp\left(w_i(\tau)' \beta + \gamma_0\right)\right] \right], \tag{2}
$$

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[9] Nakamura and Ohashi (2006) estimated the spillover effects across plants within a firm, and found that these effects are small in economic terms. Thus, we abstract the issues of multi-plant operation in the present analysis.

[10] Alternatively, one could allow a non-parametric baseline hazard by replacing $\lambda_0(t)$ with the t-fixed effects. One could also allow the inclusion of unobserved heterogeneity in survival analysis under a specific distributional assumption of heterogeneity (for example, a gamma distribution). Due to the small number of observations (88), we are unable to allow for either non-parametrics nor unobserved heterogeneity.

where the first term in the squared bracket in (2) indicates the probability of the OHF being replaced by the BOF by the R_i-th year, and the second term in the same bracket indicates the probability of the OHF remaining in use by the R_i-th year.

Table 3 presents three results obtained from estimating the conditional likelihood function (2). Specification (3-B) adds to specification (3-A) the variable of productivity difference between the old and new technologies, and specification (3-C) allows for non-linearity in the coefficient of the plant-size variable. The Chi-squared measures indicate that the models, if any, fit the data only at the margin, and in most cases we cannot reject the null hypothesis that all coefficients in the models are zero.

Specifications (3-A) and (3-B) yield precise parameter estimates of plant size. The estimated coefficient in (3-A) indicates that a one percent increase in the number of employees lowers the hazard rate of OHF use termination by 5.2 percent. The absolute value of the size estimate is reduced by approximately 20 percent when the productivity difference variable is included in the model. This results from the fact that plant size and productivity difference are positively correlated.

As defined in the previous section, the unanticipated demand shock variable is measured as the deviation from the AR(1) prediction of the industry-level steel demand. Though statistically insignificant for all specifications, the sign of the estimates indicates that the arrival of unanticipated steel demand shock would prolong the use of the old technology.

The model includes OHF and BOF capacity sizes. The estimated signs of the variable imply the effect of economies of scale in the operation of furnace technology: It appears to have taken more (or less) time for a plant to stop using the old technology when the plant owned OHFs (BOFs) of larger size. An increase in the number of years for which a plant had used OHF (BOF) technology decreases (or increases) the conditional probability of the termination of OHF use. This result is consistent with the finding concerning the production-function estimates reported in Section 3, in that the effect of experience captured by the variable dominates the effect of capital depreciation.

The first two specifications (3-A) and (3-B) assume that the effect of plant size on the survival of the OHF is the same across different size classes. Specification (3-C) relaxes the assumption and allows for non-linearity across three classes of plant size: the plant with over ten thousand, the plant with between five and ten thousand, and the plant with under five thousand workers. These variables are defined as plant size (in terms of logarithmic number of workers) multiplied by a size class dummy. The three estimates of the plant-size variables do not differ from one another, and thus justify the treatment of the variable reported under (3-A) and (3-B).

The results of the duration analysis discussed here confirm that plant size is negatively correlated with the conditional probability of terminating OHF use. The analysis, however, only considers

the duration of the OHF usage, and does not examine OHF and BOF technology usage patterns. Section 4.2 presents such an analysis.

4.2 Analysis of Intra-plant Diffusion

This section investigates the economic determinants of intra-plant diffusion of the BOF. In the previous section, the survival analysis indicated that plant size is a main factor in determining the duration of OHF use; however, it did not reveal what determines the changes in intensity of BOF use. In this section, we try to answer this remaining question.

We employ, as the indicator of the extent of intra-firm diffusion, we use the steel output (in tons) of the BOF divided by that of the OHF, presented logarithmically. The rate of intra-firm diffusion is analyzed using the following diffusion equation:

$$\ln\left(\frac{Y_{it}^{BOF}}{Y_{it}^{OHF}}\right) = \Delta^s\left(\gamma_W^s \ln\left(W_{it}^s\right)\right) + \gamma_u \Delta^s u_{it}^s + \gamma_G G_{it} + \mu_f + \eta_{it}^s, \tag{3}$$

where Δ^s denotes the difference operator for technology type, namely $\Delta^s \xi^s \equiv \xi^{BOF} - \xi^{OHF}$, and where ξ takes either $\gamma_W \ln\left(W_{it}\right)$ or u_{it}. Model (3) is constructed using the production function (1), and the derivation is described in Appendix A. Note that the literature used the proportion of the firm's capital stock that incorporates the new technology as the measure of intra-firm diffusion. Since a plant rarely has full command of a new technology immediately upon its adoption, data regarding capital in place would tend to overstate the rate of intra-firm diffusion in comparison with our data regarding capital in use.

Three sets of explanatory variables are included in (3). The vector, W, contains vintage-specific variables of capacity size and of the number of years of use, both of which are incorporated into the production function, (1). The variables for plant size (as measured by labor) and unanticipated demand shock (as defined in the previous section) along with the constant term are represented by a vector, G. Note that the variable, G, is plant and year specific, but is not indexed by s. The productivity difference between technology vintages is represented by $\Delta^s u_{it}^s$.

While we can take care of market-level uncertainty by including the variable G, other types of uncertainty, presumably specific to the firm, may also have influenced the path of intra-firm diffusion. Some firms might have accelerated the development of the BOF based on their naive expectations of market development, while other firms might have held back the penetration, because they faced greater technological uncertainty in operating the new type of furnace. Since such uncertainty is unobserved by us, we are concerned that it could create endogeneity problems, in particular in estimating the coefficient, γ_u. Firms that are susceptible to market and technological uncertainty would tend to delay BOF adoption, and thus start with larger values for productivity differences, $\Delta^s u_{it}^s$ (as noted in Figure 5). Since such uncertainty would also reduce the diffusion

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rate, the ordinary least squared estimation (OLS) method would exert a downward bias on the estimated coefficient of $\Delta^s u_{it}^s$. In response to this endogeneity concern, we include firm fixed effects, μ_f, to control for such firm-specific unobserved uncertainty. Note that because the average firm owned more than two plants (see Table 1), multiple plants receive the same firm fixed effect (as noted in footnote 1). The last term, η_{it}^s, is a mean zero error. The parameters to be estimated are γ_W^s, γ_u, and γ_G.

In the intra-firm diffusion analysis, we employ data regarding firms that operated both the OHF and BOF. In empirical implementation, the selectivity problem is made apparent by considering the expectations of (3), conditional on the selected plant i in year t:

$$E\left[\ln\left(\frac{Y_{it}^{BOF}}{Y_{it}^{OHF}}\right)|d_{it}\right] = \Delta^s\left(\gamma_W^s\ln\left(W_{it}^s\right)\right) + \gamma_u\Delta^s u_{it}^s + \gamma_G G_{it} + E\left(\eta_{it}^s|d_{it}\right),$$

where the selection indicator, d_{it}, takes 1 if plant i satisfies both $0 < Y_{it}^{OHF}$ and $0 < Y_{it}^{BOF}$ in year t. If the selection indicator is not randomly assigned, but rather correlated with unobserved determinants of intra-firm diffusion rates, the last term of the above equation does not equal the unconditional expectation $E\left(\eta_{it}^s\right)$. We assume that the latent variable that determines the selected plants in year t is normally distributed with the diffusion errors and that the selection decision is based on plant size and age, the capacity sizes of the respective OHFs and blast furnaces, and a time trend. Plants with blast furnaces were more likely to adopt the BOF, and such a likelihood would be captured by blast furnace size. A time trend is included to control for the aggregate trend of the variables. The first-stage selection regression provides an estimate of the expected value of the error, $E\left(\eta_{it}^s|d_{it}\right)$. We subsequently include the inverse Mills ratio in the diffusion equation (3). Under the assumption of normality, the intra-firm diffusion estimates, inclusive of the inverse Mills ratio, are consistent even when technology choice is self-selected.

Table 4 presents four estimation results, based on methods without (column 4-A; hereafter "no-FE") and with the firm fixed effects (columns 4-B, 4-C, and 4-D; hereafter "FE"). Specification (4-C) incorporates the self-selection bias concern into the diffusion process, while (4-D) accounts for possible nonlinearity in the plant-size variable. The last specification includes three size-class-specific variables in the same way as (3-C) does: plant size of over ten thousand workers, between five and ten thousand workers, and remaining plants. Our inferences are based on heteroskedasticity-robust standard errors. The goodness of fit measure indicates that the model fits the data well, accounting for more than 70 percent of the variation in intra-plant diffusion. The results of the Chi-squared test would reject the hypothesis that all the coefficients of the firm dummy variables are zero.

Many coefficients in (4-A) are precisely estimated. The result indicates that a one-percent increase in the number of plant workers decreases the relative output share of the BOF by less than

half a percent. The elasticity of the diffusion indicator with respect to the productivity difference between BOF and OHF is found to be 0.80. Since the larger plants were subject to smaller productivity differences, the sign of the estimate is consistent with the findings concerning the plant-size estimate. The estimate of the coefficient of unanticipated demand shock is statistically insignificant, but the sign of the estimate is coherent with the observation presented in Figure 4.

The coefficients of capacity size and number of years of technology use are also both precisely estimated. The estimates of either variable reject the hypothesis that the OHF and BOF coefficients are the same. The estimated capacity-size coefficients indicate the existence of economies of scale: the greater the BOF (or OHF) capacity, the faster (or slower) the intra-firm diffusion. The number of years of use indicates that the experience level, rather than capital obsolescence, is a main determinant of intra-firm diffusion. The results discussed here concerning the last four variables in (4-A) are qualitatively in accordance with those found in the production-function estimates discussed in Section 3.[11]

We are concerned that other dimensions of firm heterogeneity discussed earlier in this section could presumably influence the diffusion rates, and thus bias the no-FE estimates. Hence, we include the firm fixed effects and estimate the model. The FE estimators reported in (4-B) indicate that the plant-size estimate loses both statistical and economic significance. Since the number of plant workers does not vary greatly, the plant-size variable is reasonably approximated by the fixed effects. The magnitude of the estimate in the productivity-differences coefficient thus more than doubles. The estimate moves in the direction that points to the successful elimination of the endogeneity bias discussed earlier.

Specification (4-C) corrects for selectivity in technology choice. In the intra-firm diffusion analysis, we need to consider firms that simultaneously operated both OHFs and BOFs. This sampling method, although necessary in our analysis, could generate biased estimates if there existed a persistent relationship between the diffusion rate and the choice of firms in the sample. This concern would make both capacity and number of years of technology use correlate with the error in the equation. We have applied the Heckit correction procedure in the sample selection, and included the inverse Mills ratio. Including this variable and assuming normality in the distribution of the latent variable, the estimates in (4-C) will be consistent even if the selected sample is endogenous. The results under (4-C) do not indicate the problem in the sample selection. The magnitude of differences in the estimates between results (4-B) and (4-C) are not significantly different from zero. Thus, we conclude that the selection problem is not severe, probably because

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[11]Though not reported in Table 4, we also included the number of furnaces owned by plants. Conceivably, plants with more furnaces could take longer to fully replace the old technology. We found, however, that the estimated number-of-furnace variable is not statistically significant, and that including the number of furnaces does not qualitatively change the results reported in this paper.

the termination of OHF use or adoption of BOF use are not related to the intra-firm diffusion process.

The previous specifications assume that the effect of the number of plant workers on the diffusion rate is the same for all plant sizes. Specification (4-D) relaxes this assumption, and allows for the plant-size coefficient to differ by size category. The three size variables are all estimated to be insignificant, and would not reject the linearity assumption regarding the plant size coefficient that we made in the prior specifications.

It has been a common contention that the decline of the U.S. steel industry in the late twentieth century was due to its technical backwardness and slowness in adopting new technology (Adams and Dirlan, 1966; Oster, 1982). Indeed, when Japan had already converted all of its capacity to the BOF process, the United States had merely converted half of its capacity. [12] Although the estimates presented in Table 4 were obtained from the BOF diffusion process in Japanese firms, it is tempting to make inferences regarding the intra-firm diffusion of the BOF in the United States. For data availability reasons, we focus on the plant owned by U.S. Steel that first adopted the BOF: the Gary plant in Indiana. Gary remains the largest plant of the company. We simulate the intra-firm BOF diffusion path of the Gary plant using the estimates of (4-B). [13] Table 5 presents the simulated BOF share (in terms of steel output), in comparison with the shares from the largest and smallest plants in Japan. The table indicates that when all steel was being produced by the BOF in Japan, a quarter of the steel was being still made by the OHF in Gary. This slow intra-firm diffusion rate in Gary was primarily attributable to the large capacity size of the OHF: the Gary plant had an OHF capacity more than two and a half times larger than that of Yawata, the largest plant in Japan, whereas the BOF capacity of Gary was approximately 70 percent smaller in size than that of Yawata's. Strong economies of scale in the operation of the old technology would have presumably discouraged the progress of BOF diffusion in the Gary plant. While extending this analysis to the U.S. steel industry as a whole is beyond the scope of this paper, it would be a fruitful future research project to examine intra-firm BOF diffusion patterns in the United States in greater details, and compare these results with our simulated ones.

The estimates presented in Table 4 also serve as an interesting note to the literature on the relationship between productivity and the business cycle. We calculate the industry productivity by aggregating the estimates of furnace productivity, $\tau_i + \nu_t^s$, using the output share as a weight, and then plotting the productivity in Figure 6 along with the output growth rate. It is evident in the figure that the calculated industry-level productivity is counter-cyclical to the output growth

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[12] See Table 2 in Oster (1982).

[13] We took the BOF and OHF capacity data for the Gary plant from Fisher (1951), and imputed missing values by using the average values of our data. Since OHFs in the U.S. are known to be much older than OHFs in Japan, our simulated intra-firm diffusion rate would provide a lower bound of the actual rate.

path, the correlation coefficient between the variables being approximately –0.70. This finding is largely traceable to the industry practice of frequently accommodating unanticipated demand shocks by using the old and inefficient technology.

5 Conclusion

For the Japanese steel industry, the share of output produced using the new technology was limited even several years after the diffusion process had taken place. While inter-firm diffusion was the main driver early on in the overall diffusion of BOF diffusion, intra-firm diffusion began to make the main contribution a few years later. This paper concentrated on analyzing the intra-firm diffusion pattern of the new technology, a topic that has been relatively neglected in the diffusion literature.

By making use of available panel data regarding firm capital use, data that capture the adoption and use of the new BOF technology, this paper made two major contributions to the literature on intra-firm diffusion that follow from its empirical analyses. First, the paper found evidence that the OHF was used more intensively relative to the BOF when plants faced unanticipated demand shocks. Thus, intra-firm diffusion slowed upon the arrival of industry demand shocks that were unforeseen by the plants. This industry practice in furnace operation brought about counter-cyclicality in the measured productivity. Our finding accords with that of Basu, Fernald, and Kimball (2004), who found that technology improvements reduce input use. While their finding regarding contractionary technology shocks cannot be explained by standard real business cycle models, Basu, et.al. (2004) argued that the evidence is consistent with general equilibrium sticky-price models. Though their finding of little output change is not quite coherent with our finding, our paper has suggested an alternate channel by which to generate contractionary productivity.

Second, the paper identified that differences in productivity between the old and new furnace technologies play an important role in intra-firm diffusion. Taking advantage of our panel dataset, we estimated the TFP of furnace technology. We addressed endogeneity in input choice when estimating the production function. The estimated productivity by technology vintage indicated that the BOF productivity increased, while that of the OHF decreased over the study period. We associated the measured differences in productivity between the technologies with the negative relationship between plant size and intra-firm diffusion rate.

In addition to the above contributions, this paper identified some other important features of the intra-firm diffusion of the BOF. The results of the regression of intra-firm diffusion (3) indicate the importance of usage experience and of economies of scale in the operation of the furnace technology. The estimation results are robust to the presence of sample selection and endogeneity because of the existence of firm-specific uncertainty.

It would be interesting to comment on the public policy implications of intra-firm diffusion.

Analyses of diffusion policy require knowledge of whether a firm's realized intra-firm diffusion performance differs from the optimal performance, and of whether policy interventions addressing the diffusion path actually improve social welfare (Stoneman, 2001). The paper's analysis suggests that diffusion policies could be justified on the grounds that firms have insufficient information regarding the use of new technology. Our estimation results indicated that experience in furnace operation was an important determinant of intra-firm diffusion of the BOF. Indeed, approximately 30 percent of the variation in BOF diffusion could be explained by operational experience, according to our analysis. If this experience exhibits externalities that cannot be fully appropriated by the firms themselves, there must be room for public policy in intra-firm diffusion. Measuring the magnitude of the externalities that arise from the adoption and use of BOF would be the next step to understanding the need for public policy addressing technology diffusion.

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A   Derivation of the Intra-firm Diffusion Equation

This technical appendix describes the micro-economic foundation of the intra-firm diffusion equation (3) introduced in Section 4. The diffusion equation was based on the production function discussed in Section 3. We took the output ratio of the BOF to the OHF to obtain:

$$
\begin{aligned}
\ln \left(\frac{Y_{it}^{BOF}}{Y_{it}^{OHF}} \right) =\ & \sum_k \left[\beta_{X_k}^{BOF} \ln \left(X_{itk}^{BOF} \right) - \beta_{X_k}^{OHF} \ln \left(X_{itk}^{OHF} \right) \right] \\
& + \left[\beta_K^{BOF} \ln \left(K_{it}^{BOF} \right) - \beta_K^{OHF} \ln \left(K_{it}^{OHF} \right) \right] \\
& + \left[\beta_Z^{BOF} \ln \left(Z_{it}^{BOF} \right) - \beta_Z^{OHF} \ln \left(Z_{it}^{OHF} \right) \right] + \left[u_{it}^{BOF} - u_{it}^{OHF} \right]
\end{aligned}
\tag{A1}
$$

Vector X contains the variables of labor and fuels. The available labor data are not indexed by furnace vintage, because the same workers operated both types of furnaces. We thus classified labor under the variable G_{it}. Fuels (namely electricity and oil) are variables that plants could adjust when facing unanticipated demand shocks. Although varying by plant, fuels are indeed highly collinear with the unanticipated demand-shock variable. By including the variable of unanticipated demand shock in (3), we had to drop the fuels variable from the equation. We also multiplied the parameter to be estimated, γ_u, by the interest variable, $u_{it}^{BOF} - u_{it}^{OHF}$, so as to assess the impact of differences in productivity between the technologies. To account for the possible endogeneity concern, we added the firm fixed effect, μ_f, to (A1). The fixed effects control for unobserved differences between firms that do not change over time. Finally, the error term, η_{it}^s, was added to (A1) to derive the intra-firm diffusion equation (3).

B   Data Description

Our dataset comprises annual plant-level furnace data describing 13 plants and 9 Japanese steel firms from 1957 to 1970: the output and input data (except for labor and physical capital, as described below) come from Japan Steel Federation (1955–1970). The data cover approximately 95 percent of the total steel production throughout the study period. We focused on crude steel as the output. For the inputs, we collected data regarding the amounts of oil and electricity used. The output and input data identify two furnace types, OHF and BOF, for each plant. Over 90 percent of the plants covered in the data operated more than one furnace in a given year. The input and output data are aggregated over these multiple furnaces of the same vintage within a plant. The cumulative plant output by vintage is calculated for the period beginning 1947. The obtained estimation results do not change when we calculate the variable for the period beginning 1931.

Data concerning labor input are constructed from two datasets: the number of workers at the plant level (from Japan Steel Federation, 1955–1970) and the actual work hours averaged over workers at the firm level. The data concerning the number of workers are not disaggregated by furnace type, unlike the other input data obtained from the same source. This construction of the labor data is due to the fact that plant workers often operated both types of furnace. The labor input used for the estimation is expressed in terms of total man hours, which is constructed from the number of plant-level workers multiplied by the actual work hours averaged over workers at the firm level.

The data pertaining to furnace capacity by plant were obtained from companies' semiannual financial reports, which identify the capacities of all furnaces in the 13 plants covered in our data. The data recorded the capacity at the end of year t, and investment was made only when a new furnace was built. The capacity of furnace j_s using technology s, located in plant i in t changes as follows: $k_{it}^{j_s} = (1 - \delta) k_{it-1}^{j_s}$, where δ is the depreciation rate. This paper's result is based on the assumption that δ equals zero. Alternatively, we set δ to 0.05, to allow for the possibility that that furnace efficiency may have declined over time. This assumption generates similar results. For consistency with the input data described above, we aggregated $k_{it}^{j_s}$ over s to obtain the capital variable of furnace s in plant i in year t.

TABLE 1

Plant Characteristics and Output Share by Furnace Technology

	BOF				OHF				Industry Total	
	output share (%)	No. Furnaces	No. Plants	No. Firms	output share (%)	No. Furnaces	No. Plants	No. Firms	Output M tons	Annual Growth %
1957	0.7	2	1	1	99.3	83	13	9	11.83	5.42
1958	9.9	4	2	2	90.1	83	13	9	12.77	7.93
1959	10.7	6	2	2	89.3	88	13	9	18.25	42.86
1960	15.3	11	4	4	84.7	90	13	9	23.16	26.93
1961	24.6	17	7	6	75.4	90	13	9	29.40	26.93
1962	40.3	22	8	7	59.7	81	13	9	27.25	−7.31
1963	52.3	26	10	7	47.7	77	13	9	34.08	25.06
1964	58.4	30	11	8	41.6	74	13	9	40.53	18.93
1965	72.1	36	13	9	27.9	64	12	9	41.30	1.89
1966	80.8	38	13	9	19.2	53	10	7	51.90	25.67
1967	84.3	42	13	9	15.7	43	9	7	63.78	22.89
1968	92.8	43	13	9	7.2	34	8	7	68.99	8.17
1969	93.8	41	13	9	6.2	27	6	6	87.03	26.15
1970	98.0	44	13	9	2.0	9	3	3	92.41	6.18
1971	100.0	44	13	9	0.0	0	0	0	88.44	−4.29

TABLE 2
Production Function Estimates

	Est.	Std Error
OHF dummy	2.268^c	1.178
BOF dummy	6.759^a	1.801
labor^{OHF}	0.467^a	0.128
labor^{BOF}	0.268^c	0.162
electricity^{OHF}	0.265^a	0.054
electricity^{BOF}	0.050	0.051
oil^{OHF}	0.014	0.019
capacity size^{OHF}	0.366^a	0.068
capacity size^{BOF}	0.665^a	0.098
OHF Use Years	0.267^a	0.082
BOF Use Years	0.058^c	0.032
Adjusted R squared	0.9996	
No. Observations	229	

Notes:
 Fixed effects estimates are omitted from the table.
 The superscripts a, b, and c indicate significance at the confidence level of 99, 95 and 90 % respectively.

TABLE 3
Duration Analysis for OHF

	No Productivity (3-A)		With Productivity (3-B)		Nonlinearity in Size (3-C)	
	Est.	Std. Error	Est.	Std. Error	Est.	Std. Error
plant size	-5.164^b	2.520	-4.852^c	2.529	–	
plant size × (#employees $\geqq$ 10000)	–		–		-5.944^c	3.321
plant size × (5000 $\leqq$ #employees < 10000)	–		–		-5.582^c	3.209
plant size × (#employees $\leqq$ 5000)	–		–		-5.819^c	3.359
Productivity difference: $\log(\text{TFP}^{BOF}) - \log(\text{TFP}^{OHF})$	–		1.086	1.454	2.613	2.109
Unanticipated Demand Shock	-6.846	5.585	-6.850	5.527	-10.252	9.398
OHF Capacity Size	-1.515	1.123	-1.511	1.115	-2.384	1.670
BOF Capacity Size	5.316^b	2.434	4.852^b	2.558	5.970^c	3.276
Years of OHF Use	-0.918	1.211	-1.137	1.245	-3.342	2.286
Years of BOF Use	0.585^b	0.277	0.584^b	0.268	0.843^b	0.410
Chi-squared for all coefs = 0	13.84^c		13.04		12.71	
log likelihood	-19.481		-19.282		-17.531	

Number of Observation = 88

a   Significance at the 99-percent confidence level.
b   Significance at the 95-percent confidence level.
c   Significance at the 90-percent confidence level.

TABLE 4
Determinants of Rate of Intra-firm BOF Diffusion

Dependent Variable: $\ln(Y^{BOF})-\ln(Y^{OHF})$

Variable	no-FE (4-A) Est.	Std. Error	FE (4-B) Est.	Std. Error	FE with Selection (4-C) Est.	Std. Error	FE with Selection Nonlinearity in Size (4-D) Est.	Std. Error
plant size	−0.403^c	0.212	0.088	0.431	0.093	0.494	−	
plant size × (#employees≧10000)	−		−		−		−0.604	0.719
plant size × (5000≦#employees<10000)	−		−		−		−0.678	0.745
plant size × (#employees≦5000)	−		−		−		−0.679	0.791
Productivity difference: $\log(TFP^{BOF}) - \log(TFP^{OHF})$	0.795^b	0.376	1.994^a	0.744	2.005^b	0.943	2.173^a	0.772
Unanticipated Demand Shock	−1.181	0.746	−1.293^c	0.681	−1.292^c	0.689	−1.295^c	0.680
OHF Capacity Size	−1.061^a	0.173	−0.708^b	0.343	−0.705^c	0.393	−0.584^c	0.350
BOF Capacity Size	1.431^a	0.180	1.190^a	0.224	1.191^a	0.227	1.298^a	0.231
Years of OHF Use	−0.382^c	0.200	−0.066	0.343	−0.058	0.526	−0.134	0.374
Years of BOF Use	0.124^a	0.030	0.190^a	0.041	0.191^b	0.078	0.183^a	0.041
Inverse Mills ratio					0.015	0.822	−0.792	0.897
Firm Fixed Effects included?	N		Y		Y		Y	
Chi−squared (All firm fixed effects = 0)	−		25.26^a		21.87^a		13.66^c	
Adjusted R−squared	0.719		0.769		0.765		0.774	

Number of Observation = 88

a   Significance at the 99-percent confidence level.
b   Significance at the 95-percent confidence level.
c   Significance at the 90-percent confidence level.

TABLE 5
**Simulated Intra-firm Diffusion of the BOF**
Gary Plant of U.S. Steel

BOF share (%)	U.S. Gary (Estimated)	Japan		
		Largest plant (Actual)	Smallest plant (Actual)	Average share (Actual)
1963	0.1	60.7	59.4	52.3
1964	52.2	64.9	75.1	58.4
1965	63.3	70.5	86.4	72.1
1966	64.1	76.7	93.1	80.8
1967	64.8	82.9	93.9	84.3
1968	74.0	90.3	99.5	92.8
1969	77.5	92.5	100.0	93.8
1970	82.3	99.3	100.0	98.0

Note:
Throughout the study period, Yawata plant was the largest plant,
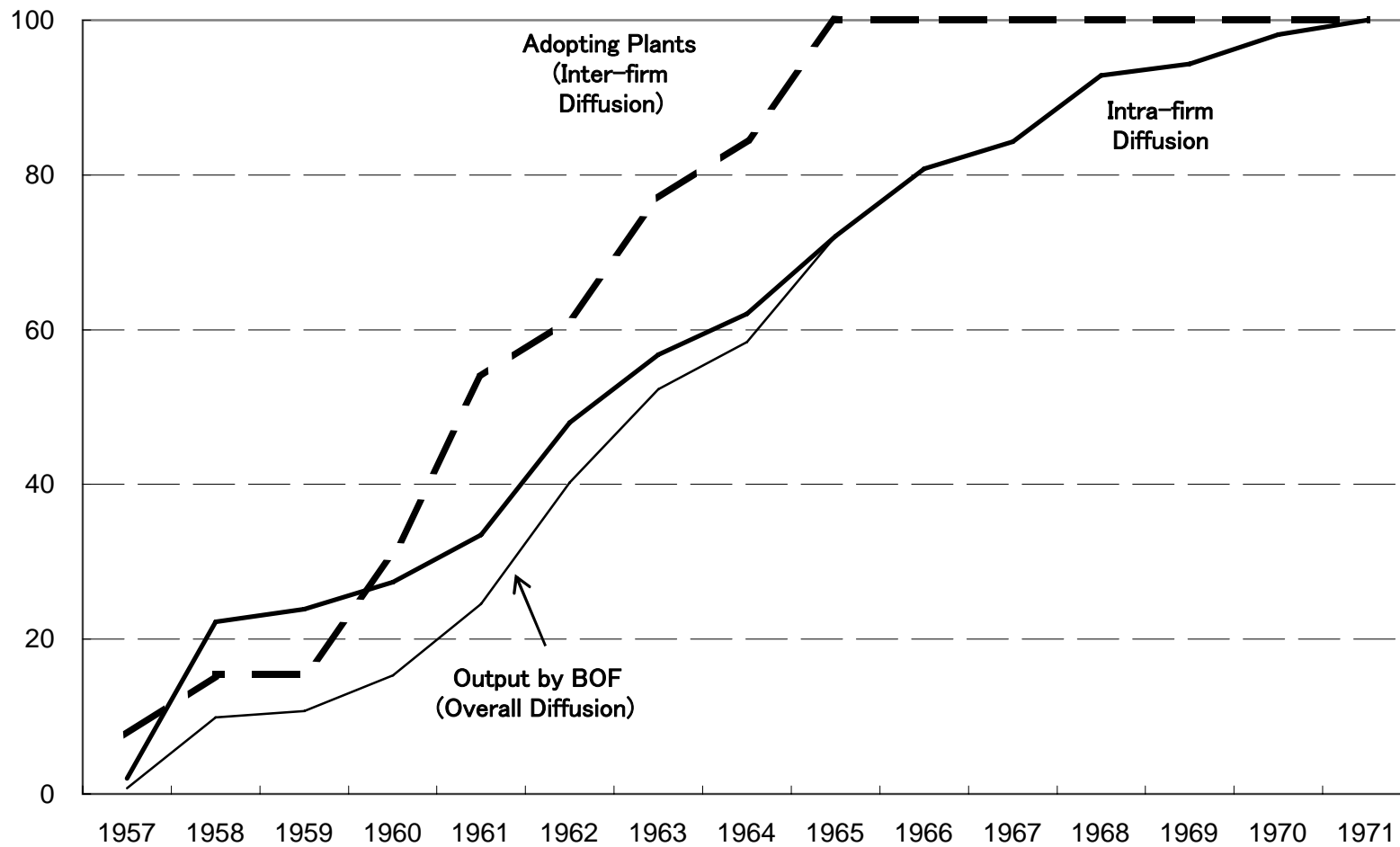and Wakayama plant owned by Sumitomo was the smallest
in Japan

FIGURE 1
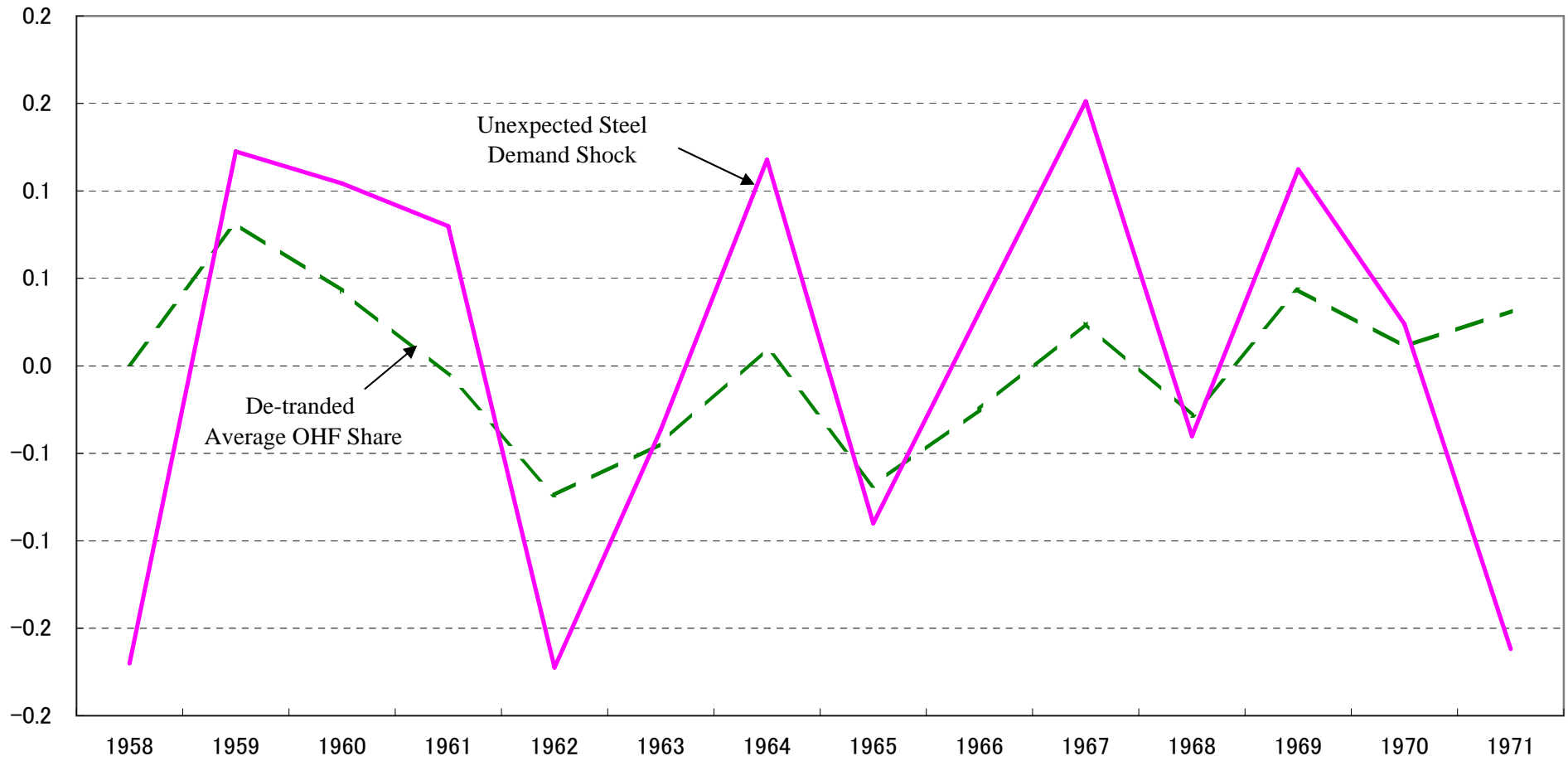**BOF Share of Steel Production by Plant**
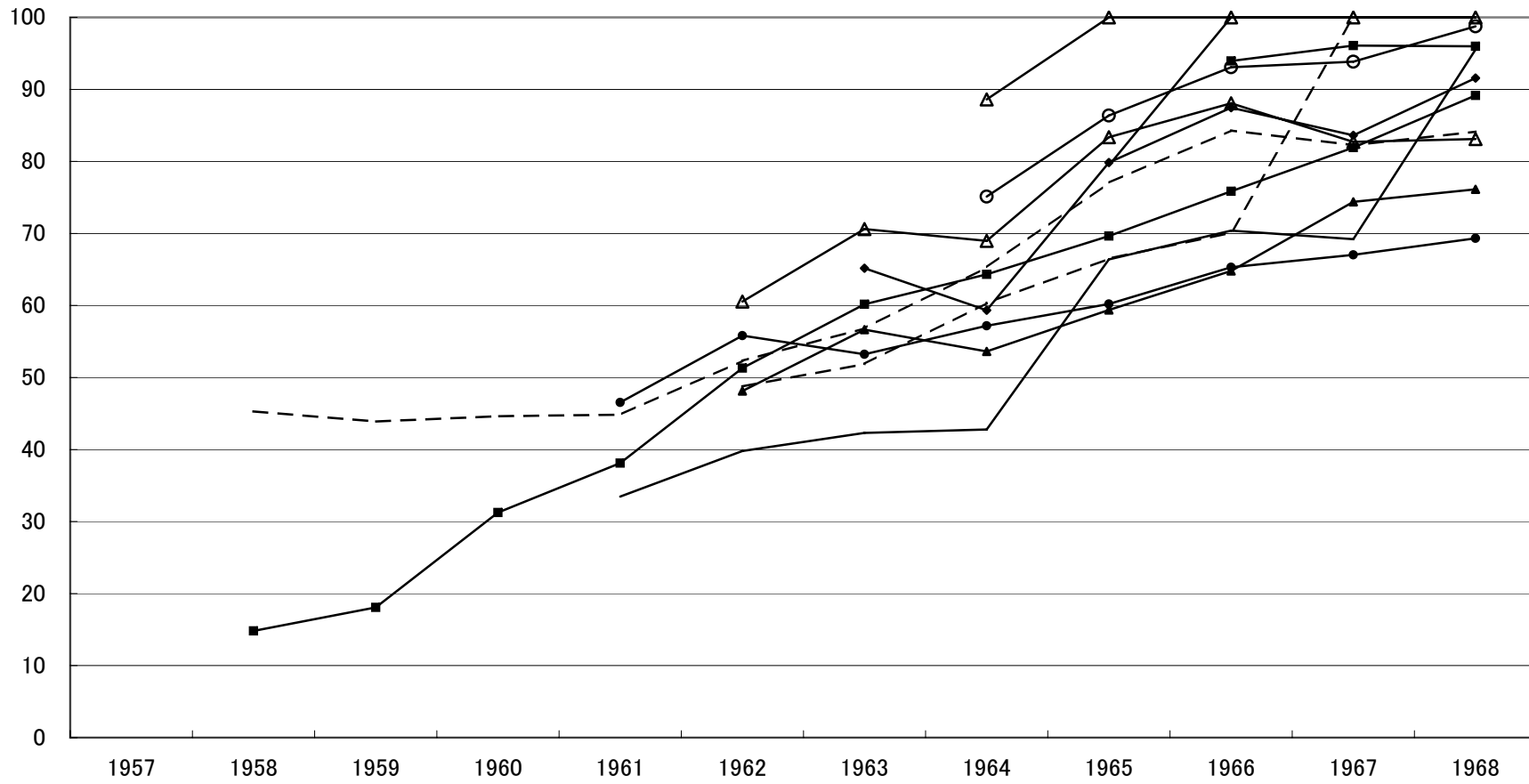
BOF Share (%)

FIGURE 2
Inter- and Intra-plant Diffusion of the BOF

BOF Share (%)

Adopting Plants (Inter-firm Diffusion)

Intra-firm Diffusion

Output by BOF (Overall Diffusion)

FIGURE 3

Plant-level OHF share and Industry Growth
in the deviation form

Deviation from
the mean

Unexpected Steel
Demand Shock

De-tranded
Average OHF Share

FIGURE 4
Relationship between Plant Size and the Rate of Intra-firm Diffusion

plant size
(log of #employees) in 1968

$y = -0.205x + 410.15$
(0.007) (151.68)

$y = 0.229x - 442.45$
(0.113) (222.85)

● BOF Adoption

■ OHF Exit
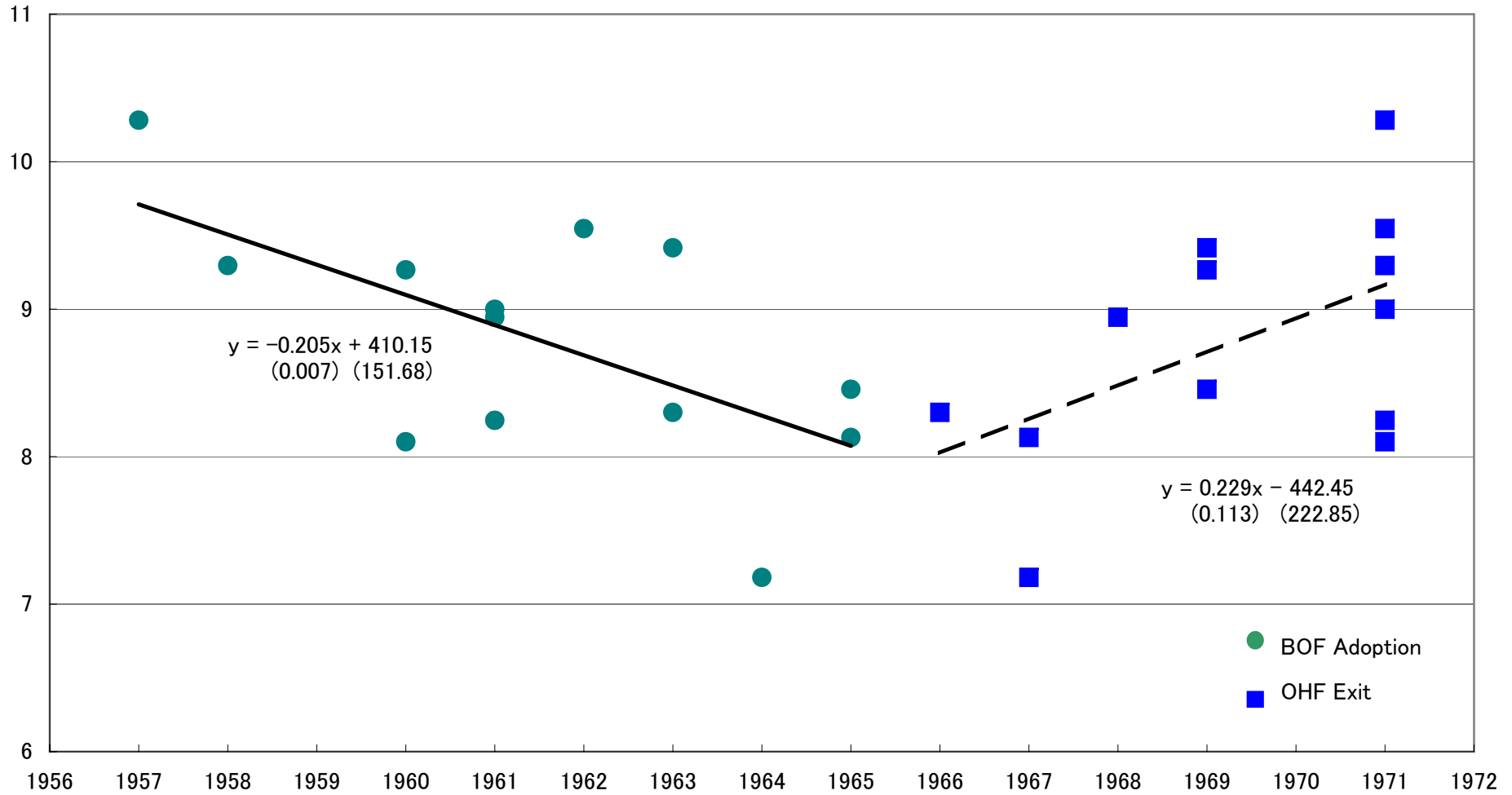
FIGURE 5
Average TFP by Technology Type (OHF and BOF)
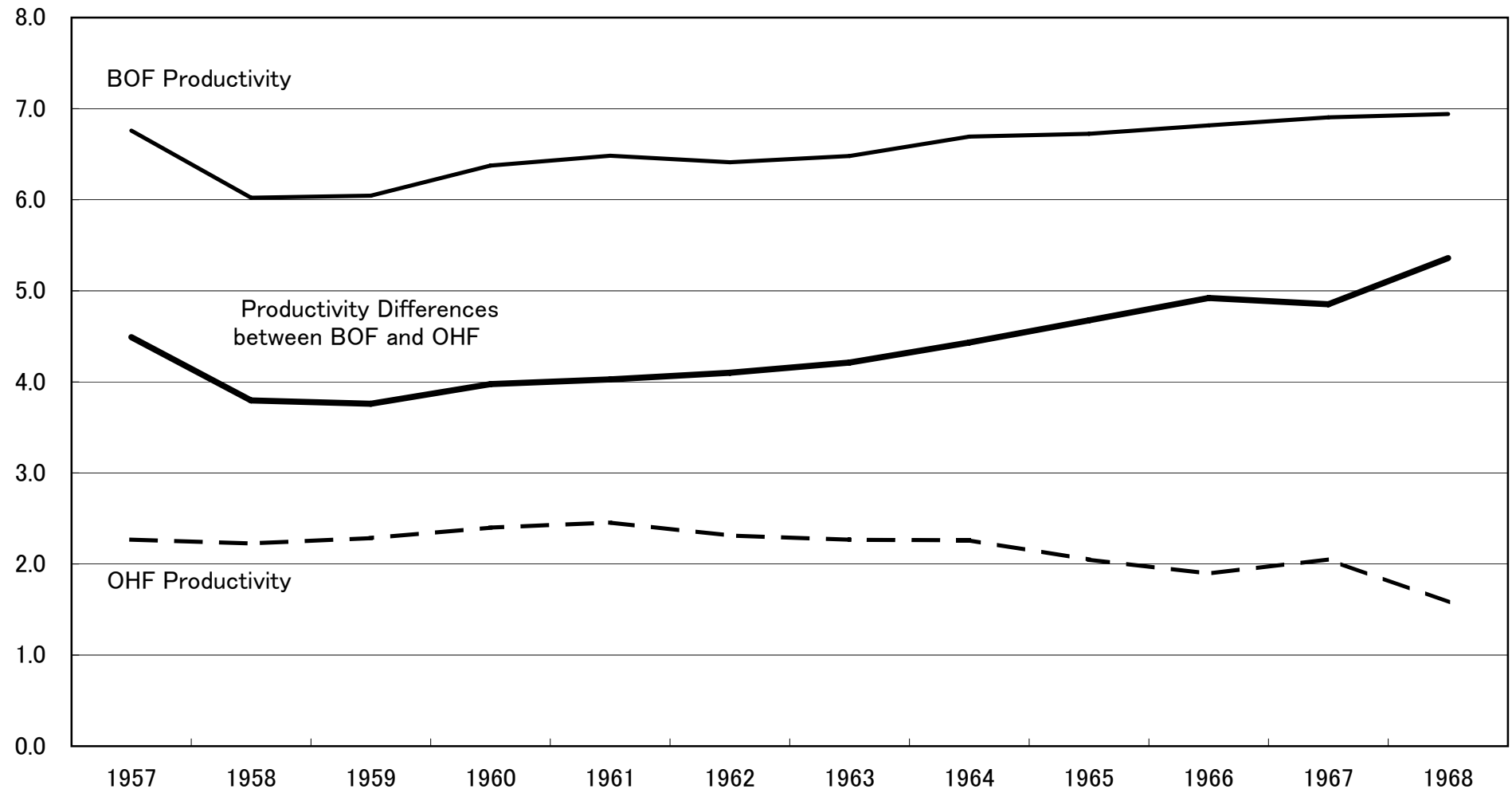
FIGURE 6
Relationship in growth rates between Productivity and Output,
from 1958 to 1968