

Effects of User Innovation on Industry Growth: Evidence from Steel Refining Technology ^{*}

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March 2008

Abstract

This paper examines the economic impact of “user innovation” — innovations developed by users instead of technology manufacturers — on industry growth and productivity. The paper focuses on two innovations produced by a Japanese steel company; these innovations improved the productive efficiency of Austrian-made refining technology, namely, basic oxygen furnace (BOF). Results obtained from the plant-level production-function estimation indicate that user innovations account for approximately 40 percent of the total factor productivity of the BOF, substantially promoting the dissemination of the BOF technology. Our simulation analysis indeed reveals that user innovations contributed to steel output growth by more than 20 percent. This paper also documents that innovating Japanese companies played the role of a “lead user” in developing and disseminating their user innovations.

Keywords: user innovation; lead user; total factor productivity; steel

JEL: O31, O33, D24, L61

1 Introduction

Innovations by users of products and processes have been frequently observed in the economy. Among many examples, the studies of von Hippel (1988) on scientific instruments and those of Rosenberg (1976) on machine tools illustrate the role of users in fostering technological progress. The concept of user innovation focuses on firms or individual consumers who expect to benefit from *using* a product or service. Thus, it is in sharp contrast to the traditional concept of innovations wherein manufacturers who expect to gain profits from *selling* are supposed to innovate. According to von Hippel (2005; 20), 10 to 40 percent of users develop or modify diverse products such as snowboards, music synthesizers, and integrated circuits. It is anticipated, especially in the area of computer software, that users’ role in innovative activity will gain in popularity with the availability of cheaper and faster communication devices (for example, see Weber, 2004). On the other hand, there is a severe paucity of empirical research that measures the magnitude of the impact of user

^{*}We thank Hiroyuki Odagiri, seminar participants at Universities of Kobe, Okayama and Tohoku for helpful comments.

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innovation on the productivity and profitability that users can avail of. Such empirical research would help quantitatively assess the importance of the concept of user innovation — a trend that has currently been featured in the literature by a number of anecdotes.

Using a unique example from the Japanese steel industry, this paper quantitatively examines the economic impact of user innovations. After the late 1950s, steel manufacturers around the world gradually upgraded their refining furnace technology, shifting from the conventional open-hearth furnace (hereafter OHF) to the Austrian-made basic oxygen furnace (BOF). While 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), several technical problems had to be resolved before the BOF technology was widely implemented. Two major problems were associated with slag slopping and exhaust gas emission. Developing improved devices to cope with these problems was imperative to ensure steel production that was cost-efficient and precise in terms of specifications and to minimize the negative environmental effects of steel manufacturing.

In response to the technical difficulties, two innovative improvements were introduced in the BOF in 1962, namely, multi-hole lance (hereafter MHL) and oxygen converter gas recovery (hereafter OG) systems: The MHL enabled substantial reduction in the frequency of slag slopping, and the OG system provided a method to recycle gas and heat generated from the steel refining stage. Interestingly, these innovations were introduced not by the Austrian, inventor of the BOF, but by a Japanese, importer and user of the technology. The two user innovations successfully improved the productive efficiency of the BOF use, and gained wide acceptance among not only domestic but also foreign steel companies. For example, by the late 1970s, firms such as U.S. Steel, Bethlehem, Armco, and Inland produced steel under the licenses of MHL and OG systems that were obtained from Japan.

To assess the contribution of user innovations on industry growth and productivity, we employ a unique plant-level data set that covers the inputs and outputs of the BOF and the installation timing and usage intensity of the innovations. The data permit estimations of the production function based on the BOF technology and of the changes in productivity, profitability, and output growth both before and after the adoption of user innovations. Our estimation results for total factor productivity (hereafter TFP) indicate that user innovations contributed to approximately 40 percent of the BOF productivity growth. Thus, the advent of steel user innovations probably facilitated the dissemination of BOF technology, thereby promoting the growth of the Japanese steel industry, as observed in Figure 1. Using simulation analysis, this paper substantiates the possibility that had the user innovations of the MHL and OG systems not been developed, the output growth of the Japanese steel industry would have averaged at only 33 percent annually, in contrast to the actual 40 percent achieved during the study period from 1957 to 1968.

Studies on innovating users show that such innovations are likely to be concentrated among the “lead users.” According to the definition proposed in von Hippel (1986), lead users are ahead of the majority of users with respect to an important market trend and that they expect to secure large benefits by proposing solutions to their leading edge needs. A close observation of innovations of the MHL and OG systems as documented in industry trade journals reveals that a company named Yawata appeared to play the role of a lead-user. As the largest steel producing firm in Japan, Yawata actively sought solutions for the technical problems of slag slopping and exhaust gas emissions resulting from BOF use. Indeed, Yawata

was the first to adopt the BOF in Japan and produced the highest share of output through BOF use during the study period; thus, it had the most number of incentives to improve the productivity of its BOF. Upon the successful development of its MHL and OG systems, Yawata freely shared the details of its innovations with other Japanese steel manufacturers, providing additional momentum to the dissemination of user innovations.¹ Our simulation analysis, based on the production function estimation, reveals that the profits Yawata secured from its innovations of the MHL and OG systems would have far exceeded those of the company with the second highest profits.

The rest of the paper is organized as follows. Section 2 provides an overview of the Japanese steel market after the World War II. It mainly describes the two innovations — the MHL and the OG systems — developed by a user of the BOF technology. Further, it illustrates that the innovating user, i.e., Yawata, exhibited the characteristics of a lead user and that it freely revealed the technical details and performance of the innovations to other Japanese manufacturers. Section 3 delineates the framework employed in estimating the productivity of user innovations. Our plant-level panel data set allows us to address endogeneity issues in productivity measurement. The estimates indicate that user innovations accounted for approximately 40 percent of the growth in steel-making productivity. Using the obtained estimates, this section also examines the steel output, considering a hypothetical situation in which no Japanese steel plants adopted user innovations during the study period from 1957 to 1968. The difference between the actual and simulated outputs is considered as the contribution made by user innovations. Finally, in Section 3, we calculate the amount of profits accrued by Japanese steel companies via user innovations. We discover that user innovations did not benefit to all companies uniformly; instead, it was the inventing company that benefitted the most. Section 4 provides the concluding remarks, followed by data appendix.

2 User Innovations and Steel Refining Technology

Japan experienced a remarkable growth in steel production shortly after World War II. Figure 1 illustrates that production in this industry expanded more than fourfold between the 1950s and 1960s. This not only satisfied the rapidly growing domestic demand but also stimulated steel exports, which grew at over 20 percent annually, raising Japan to the status of the world’s largest steel exporter in 1969.

A large portion of Japanese steel production in the 1950s and 1960s was accounted for by integrated steel manufacturers. These manufacturers processed raw materials (iron ore and coking coal) into pig iron in a blast furnace. Pig iron is subsequently converted into crude steel in another furnace by the removal of carbon and other elements. The prevalent technology used in this second or “refining” stage was that of OHF, wherein air is blown from the bottom of a brick-lined steel shell through molten pig iron. The air increases the temperature of the pig iron and oxidizes the carbon in it. In the late 1950s, the OHF began to rapidly lose ground to the BOF. Invented by an Austrian firm in 1952, the BOF technology involved the passage of oxygen for the oxidization of the iron and was expected to refine molten iron and scrap charge into steel in approximately 45 minutes—a sharp decrease from the 6 hours normally required by the OHF.

However, in achieving the full technical and economic potential of the Austrian-made technology, global

¹While it was freely disclosed in the domestic market, Yawata licensed its innovations to foreign competitors under royalty agreements.

steelmakers were confronted with two technical problems, namely those associated with (a) slag slopping and (b) exhaust gas emissions. During the refining operation, slag foam was created to improve the BOF performance. Problem (a) arose when the foam level exceeded the height of the vessel and overflowed, resulting in severe dust emissions and yield reduction. Furthermore, steel production needed to be discontinued to clean the area below the vessel and the vessel mouth. These issues motivated a search for methods to maintain a suitable foam volume, while preventing the occurrence of slopping. Problem (b) emerged when more stringent environmental standards were introduced in the late 1950s. The BOF was known to discharge the most significant level of emissions in the steel-making process. Thus, better air cleaning technology for controlling emissions was regarded as crucial for the dissemination of the BOF technology. It was primarily due to problems (a) and (b) that foreign firms, some of which had implemented the BOF earlier than did the Japanese, did not extensively adopt the technology.

These technical difficulties were resolved by two innovations introduced in 1962. One of them was the MHL, which adds more oxygen nozzles in the BOF lance to prevent slag slopping. The configuration change in the BOF lance of steel companies allows oxygen to be blown at lower velocities and thus reduces splashing in the BOF. The adoption of the MHL resulted in increased steel-making yield and improved refractory life; thus, the innovation helped facilitate the scaling up of BOF's in the mid-1960s. To solve the problem of exhaust emissions, the OG system was developed to recover gases and fumes released during the BOF steel-making process. By recycling waste gas, the OG system not only prevented pollution but also reduced energy usage. Both the MHL and the OG systems were believed to enable steel companies to achieve higher production rates with lower costs. In Section 3, we will estimate the extent to which these innovations improved the productivity of the steel refining process.

The MHL and OG systems were simultaneously introduced in Japan in 1962. Interestingly, these systems were not invented by the inventor of the BOF but by a Japanese company, namely, Yawata, which was an importer and user of the technology. As shown in the left column of Table 1, Yawata produced the largest amount of steel using the BOF technology, accounting for more than 20 percent of the total output in Japan. Hence, it is reasonable to consider that Yawata was the most incentivized to improve the efficiency of the BOF operation. Trade journals, including the Iron and Steel Institute of Japan (1982), revealed that the MHL and OG systems were the outcome of considerable experimental efforts that could only be conducted by a company with sufficient familiarity and experience in using the BOF technology.

Another interesting observation is that Yawata freely disclosed pertinent information concerning the technical details and the performance of their innovations to domestic competitors. Thus, competing firms could liberally use the released information while installing systems developed by Yawata's innovative technologies. Yawata, however, did not reveal its innovations to foreign competitors free of charge; instead, it licensed its innovations under royalty agreements with them. Although it is beyond the scope of this paper to consider as to why Yawata was so altruistic as to domestically supply such a public good, this type of free information-disseminating behavior has been frequently observed in other innovations, for example, blast furnace technology of Cleveland in the U.K. (Allen, 1983) and the Cornish pumping engine (Nuvolari, 2004).² In all likelihood, Yawata's voluntary knowledge spillovers helped disseminate its user innovations. Table 1 presents the diffusion processes of user innovations across plants. While both innovations were first

²Lerner and Tirole (2002) attempt to explain this behavior in the context of open source software development.

deployed in the same year, i.e., 1962, the diffusion paths diverged thereafter; the MHL proliferated fast and achieved full penetration across firms in 1965, when the OG system was adopted by half the existing plants. The different diffusion rates observed in the table allow us to separately identify the effects of the respective user innovations on industry growth and productivity, as discussed in Section 3.

The innovations developed by Yawata received considerable attention from foreign steelmakers as well. Although Yawata had licensed its innovations for royalty fees, the inventions were highly appreciated abroad. For example, beginning with West Germany in 1963, the OG system was adopted by more than 60 percent of the foreign steel manufacturers by the mid-1970s. Eventually, the royalties obtained from this technology by the Japanese proved to be more than the amount they had paid the Austrian company to obtain license rights for the BOF. In the next section, we quantitatively assess the extent to which user innovations contributed to the Japanese steel market in the 1950s and 1960s.

3 Economic Impacts of the User Innovations

This section, which comprises two subsections, analyzes the economic effects of user innovations on industry growth. Section 3.1 presents the method used to estimate the productivity of user innovations in the steel refining process, namely the MHL and OG systems. To achieve this, we require estimates of the production function that describes the steel refining process of the BOF. The estimation results, also presented in this section, indicate that user innovations accounted for approximately 40 percent of the TFP increase in the BOF process. Using the obtained estimates, Section 3.2 examines the steel output considering a hypothetical situation in which Japanese steel companies do not adopt the MHL and OG systems. We find that user innovations indeed contributed to the expanded steel production, and without user innovations, the output would have annually increased by only 33 percent, which is considerably below the actual output growth of 40 percent. However, the innovations did not lead to uniform benefits for all Japanese companies. In fact, our simulation result indicates that the profits earned by the innovating company, Yawata, were more than 10 percent higher than those earned by other companies.

3.1 Econometric Analysis of Production Function

3.1.1 Estimation Model

In this subsection, we empirically analyze the productivity of user innovations, namely, the MHL and OG systems, in steel production. For this, we first estimate the production function that describes the BOF steel refining process. The BOF produces crude steel of homogenous quality, regardless of whether the MHL or the OG system is installed. Our econometric model of the production function assumes the following Cobb-Douglas form (all variables are in logarithmic form).

$$y_{i,t} = \alpha_{i,t} + \beta_l l_{i,t} + \beta_x x_{i,t} + \beta_k k_{i,t} + \beta_z z_{i,t} + u_{i,t} \quad (1)$$

where $y_{i,t}$ denotes the annual output (in tons) at plant i in year t . The production function comprises several input variables. The electricity and labor inputs are denoted respectively by $l_{i,t}$ and $x_{i,t}$. The capacity size is indicated by $k_{i,t}$, and the number of years of the BOF use is denoted by $z_{i,t}$. The latter variable captures two

aspects of capital utilization. On one hand, it 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 hand, the variable indicates the degree of capital depreciation, as furnace productivity deteriorates with age. The estimated coefficient, $\beta_{i,t}$, indicates which of the two effects is more dominant in our application. The production function (1) implicitly assumes constant returns to scale across multiple BOF's owned by a plant. Our estimation results discussed in the next subsection relax this assumption and allow for discontinuity in the variables denoting capacity size and experience.

Since the MHL and OG systems contributed to improving yields and saving energy costs, we include the effect of the user innovations in the constant term, $\alpha_{i,t}$, as follows.

$$\alpha_{i,t} = \gamma_0 + \gamma_{MHL} \cdot MHL_{i,t} + \gamma_{OG} \cdot OG_{i,t} \quad (2)$$

in which $MHL_{i,t}$ (or $OG_{i,t}$) indicates the extent to which the MHL (or OG system) was instituted at plant i in year t , as presented in Table 1. Thus, either indicator takes the value in the range between 0 (when none of the BOF furnaces in plant i had adopted the corresponding user innovation) and 1 (when all furnaces at plant i adopted it).³ The Greek letters, β_l , β_x , β_k , β_z , γ_0 , γ_{MHL} , and γ_{OG} represent the parameters to be estimated.

Note that $y_{i,t}$ is measured in terms of output quantity and not value added. Many studies use value added, deflated by a common industry deflator, under the implicit assumption that the product market is perfectly competitive. If this assumption is violated and the dispersion in output prices is observed, it is difficult to obtain unbiased estimates of production-function parameters because the deflated sales differ from the actual output (Klette and Griliches, 1996).

Apart from the explanatory variables mentioned in (1) and (2), an important influence on steel production is the plant-level efficiency in production management and improvement in furnace technology, which are not directly related with the user innovations being studied herein. For example, Lynn (1982; 34) illustrates the prolonged lives of refractories through the bricks used to line the BOF's. Such unmeasured determinants are represented by $u_{i,t}$. The presence of this term may create endogeneity in input and technology choices.

Endogeneity in input choice arises when producers adjust the amount of inputs (the amounts of labor and electricity in our application) according to their efficiency differences in $u_{i,t}$. A method that fails to account for such correlation would generate biased estimates. Our response to the endogeneity problem is to use plant-, and year-specific components in the estimation — $u_{i,t} = \lambda_i + \mu_t + \varepsilon_{i,t}$, where $\varepsilon_{i,t}$ denotes a mean-zero error. The plant fixed component (λ_i) deals with efficiency differences among plants that do not change over time. The inclusion of μ_t serves to control for industry-level supply shocks. Note that year-specific components may attenuate effects of user innovations. Even though we use the panel data, the impact of innovations may be compounded by μ_t ; this is because the innovations penetrated rapidly, as indicated in Table 1. Thus, we should consider that the estimated coefficients may understate the actual impacts of the user innovations.

³We assume that $MHL_{i,t}$ (or $OG_{i,t}$) takes a value equal to the proportion of the furnaces equipped with the MHL (or the OG) systems in plant i in year t . Our estimation results discussed in this section are quantitatively unaltered under the alternative assumption that the variable takes the value of 0.5, when some but not all furnaces in plant i adopted the corresponding user innovation.

It may appear to be restrictive to assume that the plant fixed component is constant over time. However, this assumption appears reasonable with respect to our data and is consistent with the observation that the order of the plant-level production share remained constant during the sample period. Spearman’s rank correlation coefficient in terms of the BOF production share is 0.82 at the 99 percent confidence level between 1957 and 1968; moreover, the deviation from perfect correlation is entirely due to plant entry.^{4,5}

Endogeneity (or selection) in choice of technology choice arises when a firm’s decision with regard to the adaptation of user innovations is not random but correlated to the productivity, $u_{i,t}$. The severity of the selection bias depends on the magnitude of the productivity difference between plants that adopt user innovations and those that do not. In theory, two hypotheses exist with regard to the relationship between plant productivity and technology adoption. One is that the more productive plants are likelier to adopt a 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 user innovations.⁶ The alternative hypothesis is related to technology leapfrogging. For example, Jovanovic and Nyarko (1996) find an “overtaking” equilibrium in cases where less productive plants switch to a better technology more often than do more productive plants. In their model, productive plants are experienced with regard to old and familiar technologies, while the less productive plants are less attached to technologies. This extensive experience prevents productive plants from adopting a new technology, while less productive plants show a willingness to adopt it. This hypothesis suggests that less productive plants are likelier to adopt user innovations. The direction and severity of the selection bias is an empirical issue. Our specification corrects for this selectivity of furnace technology using the instrumental variable technique.

3.1.2 Estimation Results

Table 2 presents four estimation results, based on methods without (column 2-A; hereafter “no-FE”) and with the plant fixed effects (column 2-B, 2-C, and 2-D; hereafter “FE”) discussed earlier in this section. Specification (2-B) estimates (1) under the assumption of constant returns to scale across multiple BOF’s owned by a plant, while (2-D) allows for different coefficients of capital depending on the number of furnaces. Specification (2-C) responds to the concern on self-selection regarding the adoption of user innovations. 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 indicates that the model fits the data moderately well, accounting for more than 60 percent of the variation in steel output.

⁴The stability of market share is often observed in other industries in Japan. See Sutton (2005) for details.

⁵An alternative method to control for unobserved productivity is to create a proxy for u_{it} by introducing an input demand equation from outside the production-function framework. A previous version of Nakamura and Ohashi (2006) attempted to apply this method and reports 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 Akerberg, Caves, and Frazer (2005). Based on these findings in the previous version, this paper does not employ these methods to control for unobserved productivity.

⁶Our data set is unsuitable for testing a hypothesis related to wage premium and human capital. The purpose of the discussion in this paper is to illustrate the importance of controlling for self-selection in the choice of technology.

Several coefficients in (2-A) are precisely estimated; however, we are concerned about endogeneity in input choice. In particular, it is plausible that a more productive plant may be able to make more efficient use of intermediate inputs (labor and electricity) to produce a given amount of steel. This leads to a correlation between the intermediate inputs and the unobserved productivity error. The FE estimator accounts for the bias. The estimates show that the mean values of the electricity and labor coefficients are higher than those in (2-A); however, the difference is statistically insignificant.

The coefficients of capacity size and years of BOF use are precisely estimated in (2-B). The capacity-size coefficient is less than one, indicating the existence of decreasing returns to scale. The elasticity of steel output with respect to the plant-level capacity size is estimated on average as 0.38. We further examine the capacity-size variable in (2-D). As discussed in the previous section, the variable representing the number of years for which a plant had used the BOF captures the two effects. The estimated coefficient implies that the experience effect dominates the depreciation effect. If a plant uses the BOF for a duration that is greater than the mean value by one year, the steel production would increase by 5 percent.

A plant's decision regarding the adoption of the MHL and OG systems would be endogenous if there were a persistent relationship between plant productivity and the adoption timings of the innovations. This concern would make the variables of user innovations to correlate with the error in the equation (1). Specification (2-C) attempts to correct for the endogeneity in the variables of the user innovations included in (1) and (2) by using a two-stage least squared (2SLS) method. Note that the endogenous variables, $MHL_{i,t}$ and $OG_{i,t}$, are continuous, thereby indicating the extent to which the respective innovations penetrated at the plant level. We assume that the penetration of each user innovation depends on the following three variables, along with the exogenous variables included in (1), and we treat them as the instruments. First, plant age, representing the number of years for which a particular plant had operated until time t . An older plant may find it more difficult to adopt the user innovations, because the layout of the plant may not be suitable for the installation of user innovation systems. This is probably logical in that the old plant, when built, did not anticipate the introduction of the MHL and OG systems. Note that this variable differs from $z_{i,t}$, i.e., years of BOF operation, because many plants existed prior to the introduction of the BOF. The other two instruments represent the average penetration rates of the respective user innovations for the other plants owned by the same firm. It is possible that experience with user innovations may have spilled over not only within a plant but also between plants within a firm. These two instruments may be considered as appropriate in the presence of a within-firm experience spillover.

It is known that the 2SLS method can produce severely biased estimates if the instruments are weak. We thus check the explanatory power of instruments, conditional on the included exogenous variables in the first stage of the 2SLS method. Table 2 reports the values of the F-statistics for corresponding user innovations. We find that the instruments described above are not weak at the 99 percent confidence level of F-statistics. The estimated coefficients in (2-C) are obtained by regressing the dependent variable onto the exogenous and fitted values of endogenous variables. The results reported in (2-C) indicate that the model does not fit the data well, and some estimates are found to be of little statistical significance. The estimated coefficients, including those of the user-innovation variables, are statistically indifferent from the estimates reported in (2-B). To check for the endogeneity of the user-innovation variables, we compare the OLS and 2SLS estimates by the Hausman test. The results shown in the table indicate that the test does not reject

the adequacy of the OLS estimates.

Note that the coefficients of the user-innovation variables are estimated to be statistically insignificant. Based on the discussion in the previous section, we conjecture that this is due to the rapid penetration of the innovations. The effect of user innovations, particularly the MHL, is likely to be compounded by year-specific effects, μ_t , included in (1). Indeed, the first-stage regression performed in (2-C) shows that it is only the year dummy variables indicating the period from 1964 to 1968 that explain the diffusion of the MHL. Combining with the Hausman-test result, we conclude that the endogeneity in the adoption of user innovations is not severe, because such endogenous decisions are primarily explained by the year-specific components, which are already included in (2-B).

Finally, the specifications discussed so far do not explicitly consider discontinuity in capacity size and assume constant returns to scale across multiple furnaces owned by a plant that implemented the same technology. All plants possessed multiple BOF's, and the capacity size, in particular, changed only with the number of furnaces operated by a plant. In order to test whether shifting from n - to $(n+1)$ - furnace operation (where n is an integer greater than zero) changes the capital elasticity of productivity, we estimate different coefficients of capital by the number of furnaces. Due to the small sample size, we employ only the following three cases of plant operation; zero-furnace operations, one- or two-furnace operations, and operations with three or more furnaces. Thus, the model is specified as follows.

$$y_{i,t} = \alpha_{i,t} + \beta_l l_{i,t} + \beta_x x_{i,t} + k_{i,t} \beta_{k1} \times 1(0 < N_{i,t} \leq 2) + k_{i,t} \beta_{k2} \times 1(2 < N_{i,t}) + \beta_z z_{i,t} + u_{i,t} \quad (3)$$

where $N_{i,t}$ denotes the number of furnaces for plant i in year t , and $1(\cdot)$ is an indicator equal to one if the expression within parenthesis is true. Hence, β_{k1} (or β_{k2}) measures the differences in the capital elasticities between zero-furnace operations and one- or two-furnace (or three- or more furnace) operations. The other variables and parameters have already been introduced in the previous section. The estimation result is reported in (2-D). The specification uses the fixed-effect method. As observed from (2-D), decreasing returns to scale in capital are observed, and the estimated coefficients in the capacity-size variables are neither economically nor statistically different from those reported in (2-B).

The estimates in the coefficients of γ_{MHL} and γ_{OG} indicate that both user innovations improved the productivity of steelmaking. The coefficient of the OG-system variable reported in (2-B) is estimated to be significant both statistically and economically. For example, the estimates imply that Yawata, when it first installed the OG system in 1962, achieved a productivity increase of 11.8 percent.⁷ Moreover, the estimated MHL coefficient reported in (2-B) indicates that the innovation, when fully penetrated across plants, enhanced the productivity by 6.4 percent. The estimated impact of the MHL appears to be consistent with the information obtained from the trade journal. According to the Iron and Steel Institute of Japan (1982: 169), the MHL, when introduced in Yawata, boosted yield by 0.8 to 1.7 percent and shortened the hours required for steel refining by a maximum of 5 percent (i.e., a reduction of about two minutes in the refining process of approximately 45 minutes). The sum of these productivity increases, as documented in the trade journal, turns out to be similar in magnitude to that inferred from our MHL estimate.

We analyze the extent to which user innovations improved the aggregated TFP of the steel industry.

⁷Yawata installed the OG system for two BOF's out of a total of seven furnaces; thus $OG_{i,1962}$ takes the value of 0.286.

We use the estimates obtained from (2-B). Our productivity measure comprises the contributions of user innovations (represented by the second and third terms in the RHS of (2), and disembodied technical progress (represented by $u_{i,t}$). Industry productivity is calculated annually as the share-weighted average of furnace and plant productivity. Thus, user innovations are considered to improve industry productivity by the corresponding share-weighted estimates of $\gamma_{MHL} \cdot MHL_{i,t} + \gamma_{OG} \cdot OG_{i,t}$. Figure 2 illustrates that the user innovations play an essential role in the growth of industry productivity. The estimated contribution of user innovations toward industry productivity is denoted by the dotted line. This shows that the adoption of the MHL and OG systems accounts for more than 30 percent of industry productivity. The estimated industry TFP shown in the figure indicates a high correlation with steel output, wherein the correlation coefficient is 0.80. This finding corroborates with the observation made in Nakamura and Ohashi (2008), in that the adoption of BOF technology significantly promoted the growth of the Japanese steel industry in the 1950s and 1960s.

3.2 Simulation Analysis

In the previous section, our discussion was based on the production-function estimate that user innovations improved the productivity of steelmaking. In this section, we measure the impact of user innovations on the growth in industry output by examining the implications on the steel market if Japanese plants had not installed the innovations and had continued with their BOF refining operation.

We conduct the following simulation exercise to determine a plant's output level, while excluding long-run strategies such as the level of production capacity as constant.⁸ We assume no adoption of user innovations in the period from 1962 to 1968. This assumption is equivalent to both $OG_{i,t}$ and $MHL_{i,t}$ that take the value of zero, and thus $\alpha_{i,t}$ in (2) equals γ_0 . We then calculate the new plant output for each year. Since the introduction of user innovations made no changes in the technical features of the BOF steel refining process, we retain the nature of the production function (1) described in the previous section.

We assume that each plant chooses an amount of factor inputs that maximizes its own short-run profit in each year t .⁹ The production function (1) contains two factor inputs, namely, labor and electricity. We assume that labor input cannot be chosen by plants in the short-run, because most Japanese companies, including steel producers, vigorously adopted a permanent employment system. Indeed, turnover and layoffs were rarely observed during the study period. We thus consider electricity as the choice variable in the plant's optimization problem. The markets, both for steel output and factor inputs, are assumed to be competitive with regard to the steel price p_t and the electricity price ω_t .¹⁰ Hence, plant i 's profit-maximization problem in year t is given by.

⁸Our simulation exercises do not allow for plant entry and exit. It is probably unreasonable to consider that the absence of user innovations triggers a plant's entry, which is a decision that involves large sunk costs.

⁹Alternatively, we could assume that the firm maximizes its profits by solving its allocation problem across plants. Although this alternative approach may be more realistic, modeling the multi-plant feature requires complex computational issues, which are beyond the scope of this paper.

¹⁰The steel production process converts pig iron and scrap into crude steel. Thus, our price measure p_{it} is the price of crude steel, netted out of the sum of the pig iron and scrap prices.

$$\begin{aligned} \max_{X_{i,t}} & p_t Y_{i,t} - \omega_t X_{i,t} - FC_{i,t} \\ \text{s.t.} & \quad (1) \end{aligned} \quad (4)$$

where $Y_{i,t}$ and $X_{i,t}$ denote the exponential transformation of $y_{i,t}$ and $x_{i,t}$ used in (1), and $FC_{i,t}$ denotes the short-run fixed cost, including capital and labor costs for plant i in year t . To assess the counterfactual scenario, we use the estimates from (2-B) in Table 2, replacing the estimated coefficients of $OG_{i,t}$ and $MHL_{i,t}$ in (2) with zeros, and simulate the counterfactual plant output by solving the above optimization problem (4). The obtained simulated output and input for plant i is denoted by $Y_{i,t}^0$ and $X_{i,t}^0$. Following the same procedure, we simulate the model (4) with the actual values of $OG_{i,t}$ and $MHL_{i,t}$, and obtain the predicted values of the steel output for plant i , i.e., $Y_{i,t}^1$. We also denote the corresponding input by $X_{i,t}^1$. The industry outputs are calculated by summing over the obtained outputs across all plants as follows: $Y_t^0 \equiv \sum_i Y_{i,t}^0$ and $Y_t^1 \equiv \sum_i Y_{i,t}^1$. The results are presented in Figure 3. In order to facilitate comparisons among the actual output and the two output estimates, we normalize them to be 100 in the year of 1961. Note that user innovations were introduced in the subsequent year. The comparison between $Y_{i,t}$ and $Y_{i,t}^1$ indicates that the model prediction understates the actual output level; however, the annual growth rates of the two output measures are at a similar level of approximately 40 percent.

Figure 3 shows a significant contribution of user innovations to the growth of Japanese steel output. To obtain a conservative estimate, we compare the values of the simulated values of Y_t^0 and Y_t^1 . The difference between the two series diverged as user innovations penetrated across plants. The comparison of the estimates shows that user innovations increased the level of steel output by 23.2 percent, and the rate of output growth by 5 percent. When the innovations were fully distributed in 1968, the innovations enhanced the steel output by more than 28 percent. The figure illustrates that user innovations accounted for approximately a quarter of the steel output in the 1960s.

The adoption of user innovations must have been profitable because the plants voluntarily installed the MHL and OG systems. It would be interesting to examine if the benefits from plants adopting user innovations were equally obtained by firms adopting user innovations or if they were concentrated to a particular plant, especially a lead-user plant. While case studies have been conducted in the literature, including von Hippel (1986), to conclude that the latter scenario is more likely to occur, little empirical research has been available on the extent to which the innovation benefits are distributed across plants. To investigate this issue, we use the model (4) and simulate the short-run profit for each plant. We maintain the assumption of perfect competition for both the product and factor markets of steel, and assume that the values of the fixed costs, $FC_{i,t}$, are unaltered, regardless of whether or not plants installed the MHL and the OG systems. The profit accrued to plant i that adopted the user innovations is simulated as follows.

$$\begin{aligned} \Pi_{i,t}^1 - \Pi_{i,t}^0 & \equiv (p_t Y_{i,t}^1 - \omega_t X_{i,t}^1 - FC_{i,t}) - (p_t Y_{i,t}^0 - \omega_t X_{i,t}^0 - FC_{i,t}) \\ & = p_t (Y_{i,t}^1 - Y_{i,t}^0) - \omega_t (X_{i,t}^1 - X_{i,t}^0), \end{aligned}$$

where $\Pi_{i,t}^1$ (or $\Pi_{i,t}^0$) represents plant i 's simulated profit in year t under the assumption that both $OG_{i,t}$ and $MHL_{i,t}$ take the actual values (or take the values of zeros). Thus, the difference between $\Pi_{i,t}^1$ and

$\Pi_{i,t}^0$ indicates the additional monetary benefits obtained from a plant’s adoption of user innovations. The simulation results presented in Table 3 show that the inventing company, Yawata, was the largest beneficiary of user innovations; in our data set, Yawata’s benefit from the innovations was about 30 percent larger than that of the second largest beneficiary, Fuji, and eighteen times larger than that of the company that benefitted the least. This finding appears to indicate that Yawata, with the largest BOF production in the Japanese steel market, was most motivated to create the MHL and OG systems. The results from our ex-post simulation exercise analyzed in this section are consistent with the hypothesis proposed in von Hippel (1986) that Yawata fits the lead-user role in the creation of the MHL and OG system.

4 Conclusion

New technologies often appear in a rough form. A long process of improvements is usually required in order for such technologies to successfully prevail in the economy. This process of improvements occurs on the sides of both producers as well as users. In this paper, we focused on the role of users in technological improvements. It is anticipated, especially in the area of computer software, that users are playing an increasingly important role in such innovative activities. Moreover, there has been scarce empirical research to identify and assess the importance of user innovations.

Using the unique example of the Japanese steel market, this paper empirically examined the economic significance of user innovations. The paper investigated two innovations that were created in Japan, namely, the MHL and OG systems. Both innovations resolved technical problems inherent in the use of BOF steel refining technology and improved its performance. The distinctive feature of the innovations is that the MHL and OG systems were invented by a user and not by a manufacturer of the BOF. This paper examined the extent to which user innovations affected industry output and productivity. The estimates of the production function indicate that the innovations accounted for approximately 40 percent of the steel making productivity. The simulation results show that the steel output in Japan would have lowered by 20 percent without user innovations. The paper also illustrates that the benefits of user innovations were concentrated to the innovating company, Yawata. This paper subscribes to the view stated in trade journals and argues that user innovations in the Japanese steel refining process in the 1960s are consistent with the “lead-user” hypothesis proposed in von Hippel (1986). This paper corroborates that Yawata benefitted most from user innovations and states that Yawata freely disclosed pertinent information concerning the technical details and the performance of their innovations to their domestic competitors.

Although it focused on one specific example of steel refining technology, this paper quantitatively identified the fact that user innovations contributed significantly to industry growth and presumably to the economy. It is, however, important to note that the paper’s analysis is ex-post; that is, we considered successful user innovations with the benefit of retrospection. Although it is extremely difficult to collect data, one avenue for future empirical research on user innovations is to choose examples, preferably drawn from a random sample based on ex-ante perspective. This will enable the study of not only successful innovations but also failed or ineffectual innovations.

A Data Appendix

Our data set comprises annual plant-level data describing 19 plants and 8 Japanese steel firms for the period 1957 — 1968. The output and input data (except for labor and physical capital, as described below) were obtained from the 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. With regard to the input, we collected data on the amount of electricity. Over 90 percent of the plants covered in the data operated more than one furnace in a given year.

Data concerning labor input were constructed from the following two data sets: the number of workers at the plant level (obtained from the Japan Steel Federation, 1955 – 1970) and the actual work hours averaged over workers at the firm level (obtained from the Tekko Shimbun Co, 1955 – 1970). Data concerning the number of workers were not disaggregated by furnace, 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 furnaces. 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. Data pertaining to furnace capacity by plant was obtained from companies' semiannual financial reports, which identify all furnace capacities for the 19 plants covered in our data. The data recorded the capacity at the end of year t , and an investment was made only when a new furnace was built.

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TABLE 1
Diffusions of the MHL and OG Systems
Classified by Firm, Plant, and Furnace, 1957 - 1968

	Number of BOF Firms			Number of BOF Plants			Number of BOF Furnaces			Yawata's Share in Steel made out of BOF in Japan (%)
	total	w/ MHL (%)	w/ OG (%)	total	w/ MHL (%)	w/ OG (%)	total	w/ MHL (%)	w/ OG (%)	
1957	1	0	0	1	0	0	2	0	0	100.0
1958	2	0	0	2	0	0	4	0	0	51.2
1959	2	0	0	2	0	0	6	0	0	59.9
1960	4	0	0	5	0	0	13	0	0	59.8
1961	5	0	0	8	0	0	19	0	0	43.8
1962	6	50	17	9	33	11	25	24	8	34.7
1963	6	83	33	11	45	18	29	52	14	30.2
1964	7	100	57	13	92	31	35	91	23	27.9
1965	8	100	63	16	100	44	42	100	33	24.1
1966	8	100	63	17	100	41	47	100	32	24.0
1967	8	100	63	18	100	44	55	100	33	23.7
1968	8	100	63	19	100	47	59	100	34	23.1

TABLE 2
Estimates from Production Function

	no-FE			FE			FE with 2SLS			FE with Number of Furnaces		
	(2-A)			(2-B)			(2-C)			(2-D)		
	Est	Std Err		Est	Std Err		Est	Std Err		Est	Std Err	
labor	0.124	0.071	c	0.264	0.089	a	0.361	0.141	b	0.289	0.094	a
electricity	-0.034	0.039		0.139	0.041	a	0.099	0.116		0.131	0.042	a
capacity size	0.891	0.047	a	0.382	0.066	a	0.387	0.108	a	-		
capacity size (#furnaces ≤ 2)	-			-			-			0.440	0.093	a
capacity size (#furnaces ≥ 3)	-			-			-			0.429	0.084	a
Years of BOF use	0.198	0.057	a	0.211	0.061	a	0.200	0.065	a	0.216	0.061	a
<i>OG</i>	-0.225	0.086	b	0.413	0.168	b	0.950	0.825		0.383	0.172	b
<i>MHL</i>	0.011	0.151		0.064	0.078		0.072	0.372		0.042	0.082	
Plant Dummies	N			Y			Y			Y		
Selection on the User Innovations	N			N			Y			N		
Adjusted R-squared	0.90			0.79			0.68			0.80		
1st Stage F Stats for OG system	-			-			3.00 ^a			-		
1st Stage F Stats for MHL	-			-			15.21 ^a			-		
Hausman Statistics (D.F.)	-			-			1.76 (2)			-		

Number of Observations=104

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

Note: The year dummy variables are used in the estimation, but not reported in the table.
Specification (2-C) employs, as the set of instrumental variables, the number of OG systems installed in the other plants owned by the same company and plant age.

TABLE 3
Annual Profits Generated by
the Adoption of User Innovations

Yawata	1875.1
Fuji	1444.6
Sumitomo	1284.5
Nisshin	828.9
NKK	365.8
Kawasaki	306.1
Osaka	158.1
Kobe	100.0

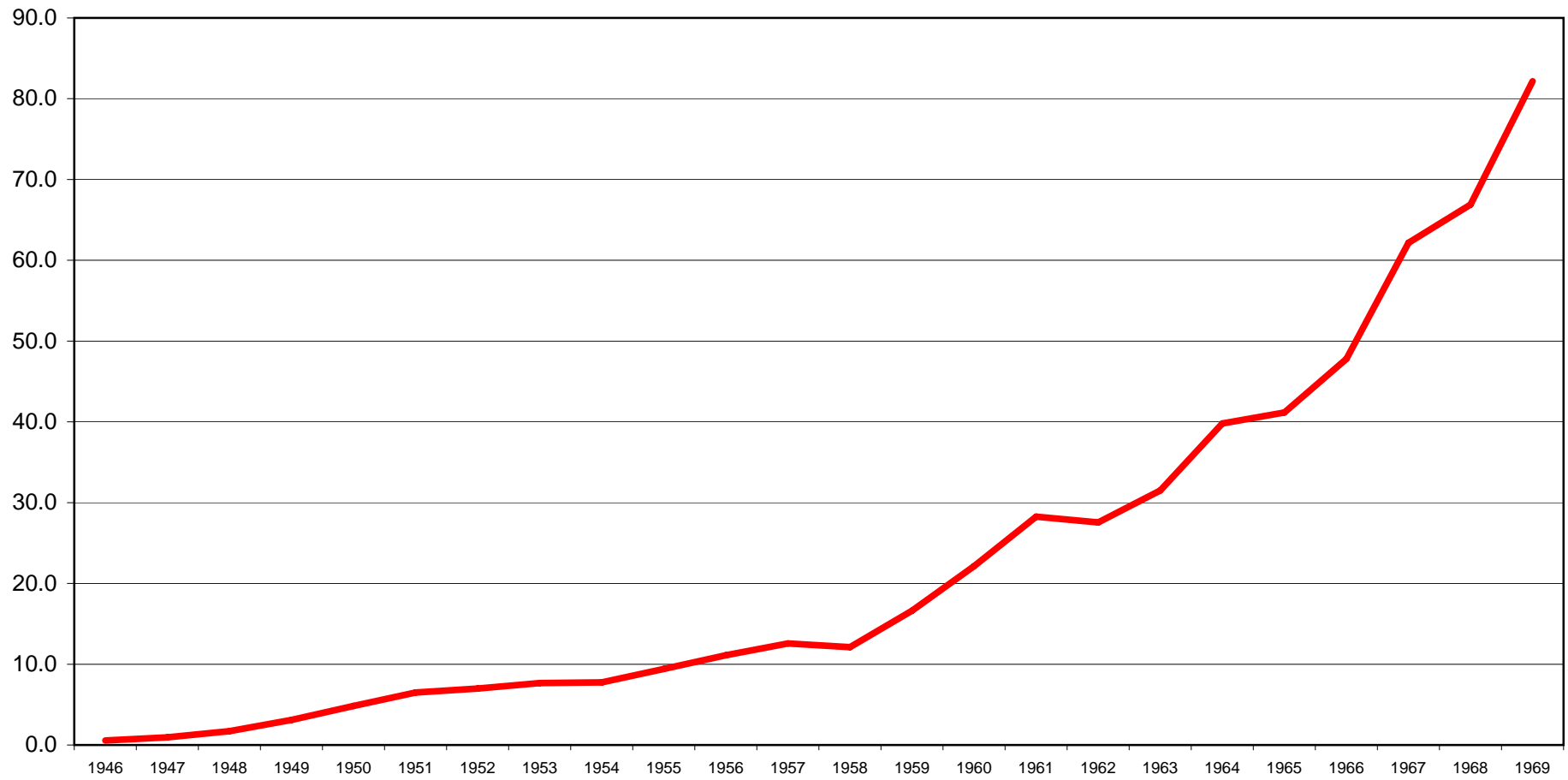
Note:

The values are obtained by the simulation method described in Section 3.

They are normalized at 100 for the amount of profit yielded to Kobe.

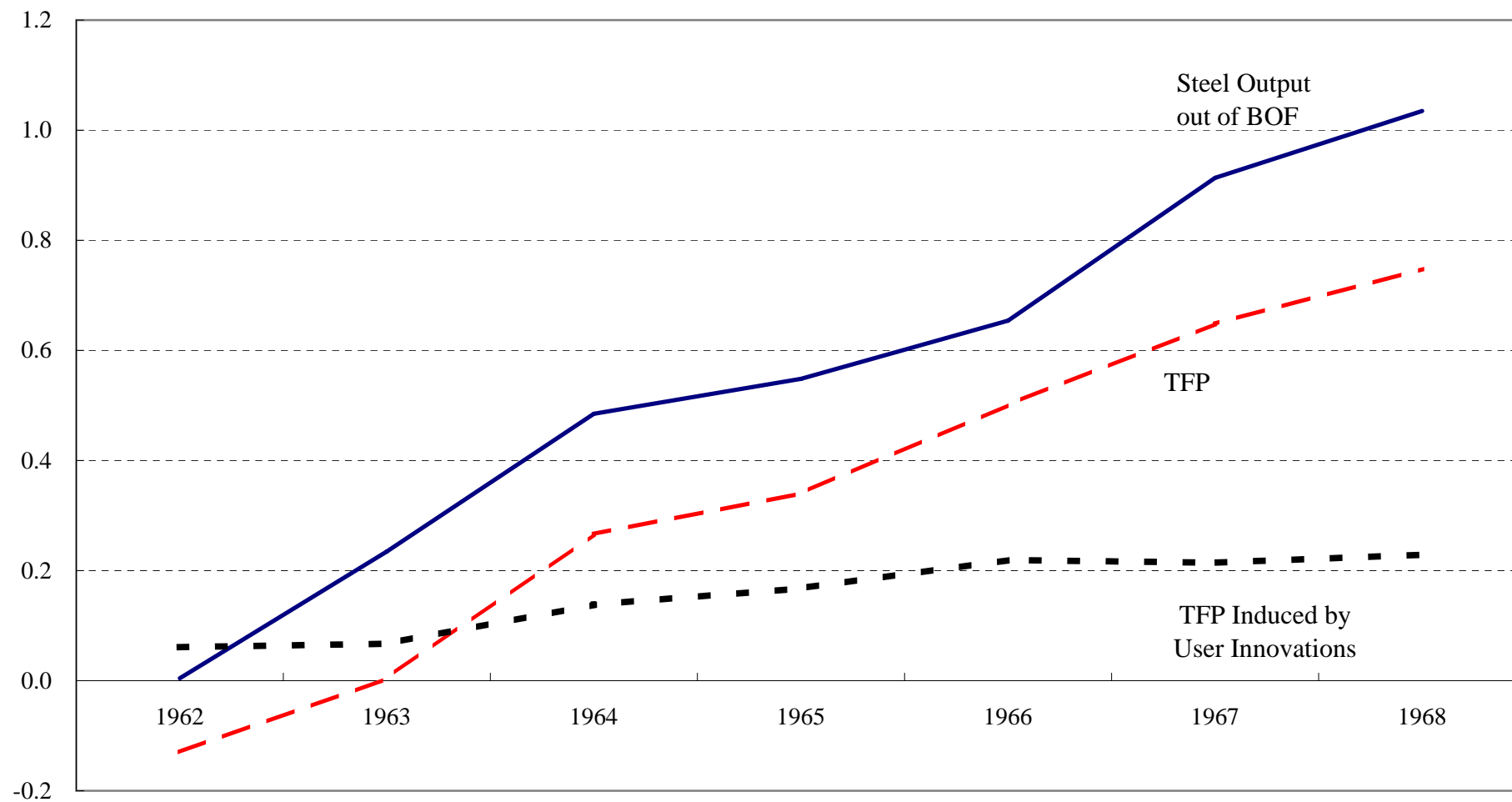
FIGURE 1
Steel Production in Japan
1945-1969

Output
Million tons



Logged Values,
Normalized by Logged
Values at Year 1962

FIGURE 2
Industry-level BOF Output, TFP, and
Contribution of User Innovations, 1962 - 1968



Normalized Steel Output
100 at Year 1961

FIGURE 3
Actual and Simulated Outputs:
Contribution of User Innovations

