

Small Steps for Workers, a Giant Leap for Productivity[†]

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We document the evolution of productivity in a steel mini mill with fixed capital, producing an unchanged product with Leontief technology working 24/7. Despite—almost—unchanged production conditions, output doubled within the sample period (12 years). We decompose the gains into downtime reductions, more rounds of production per time, and more output per run. After attributing productivity gains to investment and an incentive plan, we are left with a large unexplained component. Learning by experimentation, or tweaking, seems to be behind the continual and gradual process of productivity growth. The findings suggest that capacity is not well defined, even in batch-oriented manufacturing. (JEL D24, D83, G31, J24, L23, L61)

Productivity growth and dispersion are of great importance for the understanding trade, business survival, and economic growth. While recent empirical work (surveyed in Syverson 2011) has documented substantial heterogeneity across plants, and changes over time (Asker, Collard-Wexler, and De Loecker 2012), there is little agreement about the source of these differences and changes. The main hurdle to quantifying the evolution of productivity, and its determinants, is the availability of data, good enough to match the complexity of the measurement challenges. Griliches (1996) provides a history of the issues faced by the literature since its beginnings. The challenges range from conceptualizing good managerial practices to properly measuring inputs and outputs. Firms typically produce a range of products of varying prices, and it is not obvious how to aggregate them into a single output measure.

In this paper we try to shed some light on the sources and evolution of productivity growth by looking at a single firm, for which we have access to very detailed data. We study a steel melt shop that uses a very traditional, arguably Leontief, technology. Despite the absence of dramatic changes in economic conditions, the melt shop almost doubled its output over a 12-year period. While studying a single plant limits the take away, the simplicity of the product avoids many of the common measurement challenges. First, the melt shop produces a single homogenous product, steel billets, which is a well-defined, internationally traded commodity.

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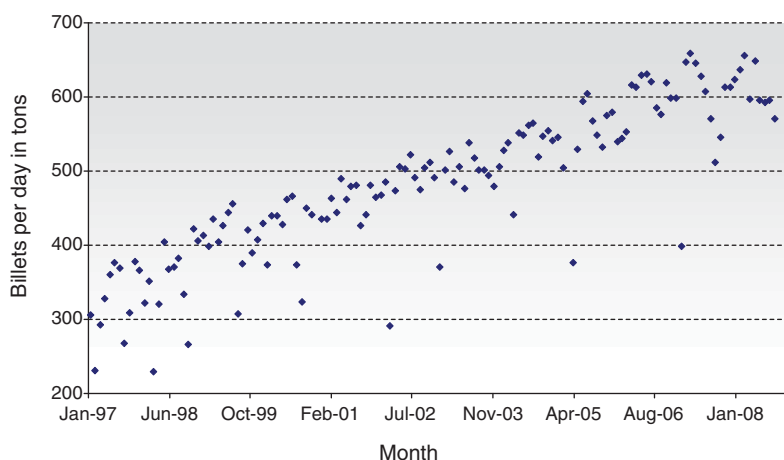


FIGURE 1. MONTHLY AVERAGE OF DAILY PRODUCTION OF BILLETS IN TONS, JANUARY 1997–SEPTEMBER 2008

Hence, we are able to cleanly measure output in physical units (as opposed to revenue or bundles of products). Second, capital is also well defined: the melt shop used the same furnace throughout the sample period, meaning that capital, and thus capacity, remained fixed. Third, while labor quality and heterogeneity is typically a concern, the melt shop suffered almost no labor turnover, and kept working in three daily eight-hour shift, on a 24/7 basis, virtually throughout the entire sample period. Fourth, we were granted access to very detailed production and cost data (even daily input utilization and output for part of sample period) that enabled us to decompose the source of the productivity gain in an unusually detailed way.

Figure 1 shows the monthly average of the daily production of billets in tons over the sample period.¹

Figure 1 displays several remarkable facts. First, the daily production of billets doubled in a span of almost 12 years. This is especially striking given that there were no major changes in production conditions. Second, while the steelmaker improved the furnace (though did not change its size) and introduced an incentive scheme for its employees, we do not spot jumps in output commensurate with discrete production enhancements. Third, output growth is continuous, suggesting that a flow of small improvements to the production process took place. It appears as if small improvements, or “tweaks,” might be necessary to exploit the potential gains created by new equipment or practices, otherwise jumps would be observed.²

We propose a production function, at the heat level, which suggests a natural output decomposition. This decomposition shows that output increases, despite not

¹We show the monthly average of the daily production level (rather than the monthly production levels) to eliminate fluctuations in total production levels from one month to another due to month length.

²Indeed, the steelmaker’s management, as well as other experts we talked to, stressed that production involves many trade-offs, which require a lengthy trial and error process and tweaking in order to discover the optimal way to produce. See Section VII for some specific examples. The notion that “tweaking” existing technologies can be an important source of economic growth and technological progress is advanced in Meisenzahl and Mokyr (2012) who stress the importance of “tweakers” to explain the technological leadership of Britain during the Industrial Revolution.

changing the size of the furnace, through: (i) an increase in plant utilization by cutting the number and length of shutdowns,³ (ii) an increase in the number of heats per day of operation (“effective day”), and (iii) an increase in the billets output per heat. We relate the timing of the improvement in the three components to the timing of the different innovations (physical and worker incentives). The goal is to attribute the gains to specific changes, and as a by-product to figure out what proportion of the overall gain in productivity remains unexplained by these actions. We find that about 15 percent of the increase in production can be attributed to several capital investments. Capital investments affected production through heats per day and billets per heat, but seem to have only a very minor effect on plant utilization. Another 18 percent of the increase in production can be imputed to the incentive scheme. The scheme seems to have had a large positive effect on heats per day, a small effect on billets per heat, and a large negative effect on plant utilization, though the positive effects outweigh the negative one. The remaining unexplained growth in production, which cannot be attributed to observed changes, is quite substantial and amounts to a 3.06 percent annual productivity growth as measured by the evolution of value added.

We do not know what enabled the unexplained productivity growth. Conversations with management suggest that they believe the productivity gain can be attributed to “learning through experimentation” or “tweaking the production process.” For instance, experimenting with the way scrap is fed into the furnace and in the timing of the different tasks performed. This form of learning is driven by how production takes place, trying new ways to execute each step of the production process. Although we do not have direct evidence that tweaking was behind the observed growth, the many different stories from the steelmaker’s management about little improvements that were introduced over time, and the fact that growth was gradual and continuous, lead us to believe that tweaking is a plausible explanation.

Our findings suggest, however, that experimenting with the production process can expand capacity substantially, even when physical capital is fixed and the technology is quite traditional. Capacity seems to be a more stretchable, elastic, yardstick. Moreover, it appears that microinnovations (Mokyr 1990) are necessary to fully exploit physical changes. Standard production function estimation may miss the actual impact of capital improvements or other innovations, if such improvements require time consuming experimentation to bear fruits. Output may be slow to respond to investment, making it difficult to estimate its impact on production.

I. Related Literature

The process of gradual increase in output despite the lack of investments is referred to in the literature as the “Horndal effect.” The effect was introduced by Lundberg (1961) who observed that productivity at the Horndal steel works in Sweden increased by 2 percent per year, on average, between 1935–1950, despite

³As mentioned earlier, the melt shop was active on a 24/7 basis throughout the sample period. When the furnace is not active due to planned or unplanned shut downs, the workers engage in repairs and maintenance work, so the melt shop is still active even if it is not melting scrap and casting of billets.

the lack of significant capital investments. David (1973, 1975) documents a similar effect in a textile mill in Lowell, Massachusetts, from 1835 to 1856.

The experiences at Horndal and Lowell are puzzling and received a lot of attention from economists. Arrow (1962) argues that the productivity growth at Horndal is due to “learning from experience” and David (1973, 1975) makes a similar argument about the experience in Lowell. Later papers, however, argue that the Horndal effect is due to more complex factors than simple learning from past experience. Genberg (1992) attributes the Horndal experience to minor alterations to the capital equipment, the introduction of organizational change, and increased effort by labor. Lazonick and Brush (1985) argue that the productivity growth at Lowell was due to social factors and improved management-worker relations, while Bessen (2003) argues that it was due to a switch to more experienced workers.

In a similar vein, Thompson (2001) claims that a large part of the productivity gains in shipbuilding during World War II, which were previously attributed to “learning,” were actually due to massive, unmeasured, capital improvements.⁴ Tether and Metcalfe (2003) document a Horndal effect in some of Europe’s most congested airports in the 1990s,⁵ and attribute it to learning through ongoing interaction between different teams that specialize in specific tasks.

Like us, two recent papers also document significant productivity increases in a single plant. Das et al. (2013) studies the largest rail mill in India between 2000–2003, where average output per shift increased by 28 percent, the number of defects was cut in half, and delays caused by employee errors went down by 43 percent. They attribute over half of the increase in output to productivity training to avoid employee mistakes and machinery malfunctioning. Finally, Levitt, List, and Syverson (2012) study an assembly plant of a major auto producer and find that defects per vehicle fall more than 80 percent in the first 8 weeks of production. Unlike in our case, gains occur in a matter of weeks.

II. Background and Production Function

Our study and data focus on the production of billets in the melt shop of a vertically integrated steelmaker. The melt shop uses a traditional mini mill technology, which has been in commercial use since the early 1900s.⁶ Production at the melt shop begins with layering processed scrap into a basket according to size and density. The scrap is then charged into an Electric Arc Furnace (EAF) through a retractable roof. An electric current is then passed through electrodes to form an arc, which generates heat that starts the melting process. To accelerate the melting process, oxygen is blown into the scrap, and other Ferro alloys are added to give the molten steel its required chemical composition. During the heat cycle, which lasts for about an hour,

⁴Thompson (2001) also shows that the quality of ships, as measured by the fracture rate, declined systematically with labor productivity and production speed. Hence, simply measuring productivity by looking at the number of ships that were produced overstates the true productivity growth.

⁵For example, Heathrow’s runway capacity grew by 14 percent during the 1990s, without changes to runway system and despite the experts’ belief that there was no further scope for expansion.

⁶The mini mill technology became widely used only in the 1980s following the success of Nucor, which is by now the largest steelmaker in the United States. For a broad overview of the steel industry, see Scherer (1996). Collard-Wexler and De Loecker (2012) study the productivity gains due to transition to mini mills in the United States.

the retractable roof of the furnace is opened twice more and two additional rounds of scrap baskets are charged into the EAF. At the end of the heat cycle, the molten steel is poured into a preheated ladle furnace (LF), where it undergoes metallurgy refining treatments for precision control of chemistry. The molten steel is then moulded into billets in the continuous casting machine (CCM). The billets are then rolled in a rolling mill to produce concrete reinforcing bars (rebars), which are an important input in the construction industry.

The steelmaker uses the entire production of billets in house to produce rebars. If the billets production is insufficient, the steelmaker buys additional billets in the market. Steel scrap, billets, and rebars are all relatively homogenous products, which are traded on world markets and their prices are quoted on a daily basis in various trade publications.

A. The Production Function

Production functions reflect the output produced by a given amount of inputs, like labor, capital, and energy. The textbook description of production functions does not explicitly state the time period during which output is being produced. But implicitly the production function refers to a time period during which the inputs are dedicated to production. We will make explicit reference to time.

As mentioned earlier, production at the melt shop is organized in batches, called heats. It is thus natural to model the production function at the heat level. Arguably, production at the heat level involves a Leontief technology, as the output of each heat, measured in tons of billets per heat, y_h , is limited by the scrap and Ferro alloys inputs that are fed into the EAF, as well as by the EAF's capacity to melt scrap, the LF's capacity to process the melted scrap, and the CCM's capacity to cast the billets. The production technology can therefore be represented as

$$(1) \quad y_h = \min \{a_{EAF} \cdot k_{EAF}, a_{LF} \cdot k_{LF}, a_{CCM} \cdot k_{CCM}, a_s \cdot s\},$$

where s represents the scrap and Ferro alloys inputs, k_{EAF} , k_{LF} , k_{CCM} , represent capital—or capacity—associated with the EAF, LF, and CCM, and a_s , a_{EAF} , a_{LF} , a_{CCM} are the Leontief coefficients.

The time it takes to complete a heat clearly depends on energy used (both electric and chemical), the number of workers, the speed with which they work, how diligent they are (which is likely to cut on the number and severity of human errors), and their know-how. Let $g(e, l, s, A)$ denote the time required to complete a heat as a function of energy, e , labor input l (including the number of workers, their effort, motivation, and diligence), and productivity (or know-how) in terms of speed of production unaccounted by inputs, A . Then, the number of heats the firm can perform during a day is

$$(2) \quad h(e, l, s, A) = \frac{24}{g(e, l, s, A)}.$$

Let us denote by U the plant utilization in a given time period (a month or a day depending on whether we use monthly or daily data), measured by the total number

of hours of plant operation during that period, divided by the number of hours in the same period. Plant utilization is determined by shutdowns, due to disruptions, repairs, and maintenance.

The three components: plant utilization, U , heats per day, $h(e, l, s, A)$, and billets per heat, y_h , can be combined to define the production function, as usually represented, in terms of output per inputs during a period of time

$$(3) \quad y = F(U, e, l, \mathbf{k}, s, A) = U h(e, l, s, A) \min \{ \mathbf{a}_k \mathbf{k}, a_s s \},$$

where \mathbf{a}_k represents the vector $(a_{EAF}, a_{LF}, a_{CCM})$ and \mathbf{k} represents the vector $(k_{EAF}, k_{LF}, k_{CCM})$. The variable y , which is our measure of output, is the daily average output of billets in tons. We compute it by dividing the monthly output of billets in tons by the number of days during the month. As mentioned earlier, we use this measure in order to account for the fact that some months have 31 days and, hence, have more output than months with 28–30 days.

The Leontief part of (3) represents the bottlenecks in the production of billets in each heat, namely, capacity and scrap. The Leontief part is augmented by a function of e and l , which captures the number of heats per day, dictated by the time it takes to complete each heat. Finally, output increases linearly in utilization, U , as more heats can be accommodated the more the capital is utilized. Technological progress in output at the heat level is captured by changes in a_k , while progress in the time it takes to complete a heat is captured by A .

The production function suggests that improvements in output come either through (i) better utilization of capital (the melt shop), (ii) an increase in the number of heats per day, and (iii) an increase in the output of billets per heat.

While we would like to estimate the production function in (3), both labor and capital are fixed, aside from some improvements, during our sample. So there is not much scope for estimating a production function. Instead, we will regress each of the components, plant utilization, heats per day, and billets per heat, on the main events that took place at the plant, using the production function in (3) as framework to interpret the different improvements. For example, one would expect the incentive scheme to enhance labor in (2), while physical improvements are likely to enter through (1).

III. Data

The melt shop was acquired by the current owner several years before 1997, the start of the sample. Interviews with the steelmaker's CEO indicate that production did not change much from the acquisition until 1997. During this period, the new management team was mainly occupied with figuring out how to operate the melt shop efficiently and improving relationship with the work force (that were strained under the previous management).

We have daily data from May 2001 to August 2009 (though daily data is missing for June 2001) on production, output, every input utilized, and the time spent on production and on delays. In what follows, we will study data only until September 2008, the pick of the financial crisis. The reason to stop at this point is that the crisis had an impact on the profitability of production. Following September 2008, the melt shop

chose, for the first time at least since January 1997, to operate at less than full capacity. For January 1997 to April 2001, we only have monthly data on production.

Using the daily data, we define plant utilization as the number of plant hours in a given day divided by 24. In the monthly sample, plant utilization is computed by dividing the total number of plant hours in a given month by the total number of hours during the same month. Our measure of “heats per day” reflects the number of heats per “effective day of operation” (i.e., full 24 hours of operation).⁷ Finally, we compute “billets per heat” by dividing the output of billets in tons in a given time period (day or a month) by the total number of heats during that period.⁸ The next table shows summary statistics of the production data.

On average, the melt shop was operating for 652.3 hours a month, which amounts to 27.2 effective days of operation; performed 589.3 heats per month, which amounts to 21.6 heats per effective day; and produced 14,520.8 tons of billets a month, using

TABLE 1—SUMMARY STATISTICS: PRODUCTION (*All variables are per month*)

	Observations	Mean	SD	Min	Max	Dates of observations
Plant hours	140	652.3	84.6	113	728	Jan 1997–Sep 2008
Heats	140	589.3	112.8	107	764	Jan 1997–Sep 2008
Tons of billets	140	14,520.8	3,323.5	2,656	20,345	Jan 1997–Sep 2008
Scrap used in tons	140	16,530.1	4,095.2	3,067	24,291	Jan 1997–Sep 2008

Note: Dec 2000 is missing.

16,530.1 tons of scrap. The average ratio between tons of good billets produced and tons of scrap used as an input (called the “yield rate”) was then 88 percent.⁹ Scrap accounts for more than a half of the total cost of billets. The next large cost driver is electricity, which accounts for about 10 percent of total cost. Labor (both regular workers and subcontracted labor) account for about 8 percent of total cost, and Ferro alloys and maintenance account for slightly over 4 percent each.

A. Investments

Over the sample period the steelmaker invested about \$25 million in the melt shop. This amounts to about 3 percent of the total value of billets produced over that same period. While we do not have a complete breakdown of investment, we do know the timing of a couple of specific improvements. It is possible that other improvements were undertaken.

⁷ Accordingly, when we use daily data, we compute “heats per day” by dividing the total number of heats in a given day by the percentage of time during that day that the plant was up and running (the number of plant hours during that day divided by 24), and when we use monthly data, we compute it by dividing the total number of heats in a given month by the number of effective days of operation during that month (the total number of plant hours during the month divided by 24).

⁸ In computing the averages, we eliminated from the computation of billets per day and plant utilization some months in which the melt shop was shut down for planned renovation. These months include March 1998, March 2002, January 2003, March–April 2005, February 2007, and October–November 2008.

⁹ Most of remaining 12 percent is slag (oxidized impurities), which is sent to a landfill, and the rest is dust, which is sold to a cement producer as raw material.

Major upgrades require shutting the plant down. Since we have daily data for most of the sample period, we know when the melt shop was down. We will date all periods during which the melt shop was not operating, and use them to estimate whether breaks (jumps) in production are associated with the downtimes.

For the period January 1997 to June 2001, we only have monthly data and hence cannot identify specific downtimes. Still, we can identify seven months (March 1997, September 1997, March 1998, October 1998, August 1999, February 2000, and September 2000) during which plant utilization was substantially below the average utilization during the same calendar year.¹⁰ These low levels of utilization might indicate downtimes associated with investments.

Using the daily data from July 2001 onward, we identify the following downtimes. For some events we also know the specific investment that took place:

TABLE 2—PRODUCTION DOWNTIMES, JULY 2001–SEPTEMBER 2008

Period	Type of investment
March 17–27, 2002	Unknown
Jan. 19–26, 2003	Replacing EAF transformer
June 5–7, 2003	Unknown
Apr. 19–22, 2004	Unknown
March 6–Apr 6, 2005	Replacing LF transformer
Feb. 4–13, 2007	Unknown

B. The Incentive Scheme

In March 2001, the steelmaker introduced a new incentive scheme, meant to boost worker productivity. The scheme was then gradually adjusted over the next few months and was finally instated on June 2001. Since then, the scheme was adjusted twice following major investments. The scheme is a group incentive program, based on the daily average of tons of billets per plant hour (i.e., on heats per hour, $\frac{h(e, l, s, A)}{24}$, times billets per heat, y_h). One may wonder how group incentives, which are not associated with individual performance, and not even tied to the performance of a specific shift (but rather all three shifts working during the day), can affect performance. This type of incentive scheme is common in mini mills, given that production involves team work.¹¹ Conversations with the melt shop's management reveal that the main role of the incentive scheme is not to alleviate moral hazard in the usual sense, but instead to induce the workers themselves to drive out weak workers who hold the entire group back.¹²

¹⁰Plant utilization in these seven months was at least 10 percentage points below the average during the same calendar year. Using the same criterion perfectly identifies the months during the July 2001–September 2008 period for which we know of major shut downs from the daily data.

¹¹For instance, Boning, Ichniowski, and Shaw (2003) study data on nearly all US rolling mills operating in steel mini mills, and find that by the end of their sample period, group incentive pay plans were used by 91 percent of all rolling mills.

¹²Quote from management: "As the three stages of melting—scrap melting, refinement, casting—are performed sequentially, there exists a strong downstream dependency among them. There is not so much a problem of free riding than one of weak links in the chain causing plant performance to deteriorate. We had such cases in the past

Each day in which billets per hour is below some predetermined threshold, Q_0 , the workers receive only a base salary. The workers of all three shifts that day receive a bonus for each ton of billets above Q_0 . The bonus is moderate for output levels between Q_0 and Q_1 , the slope is w_1 , and then it becomes steeper between Q_1 and Q_2 , with slope w_2 . At Q_2 the bonus is maxed out. The incentive scheme is illustrated in the following figure:

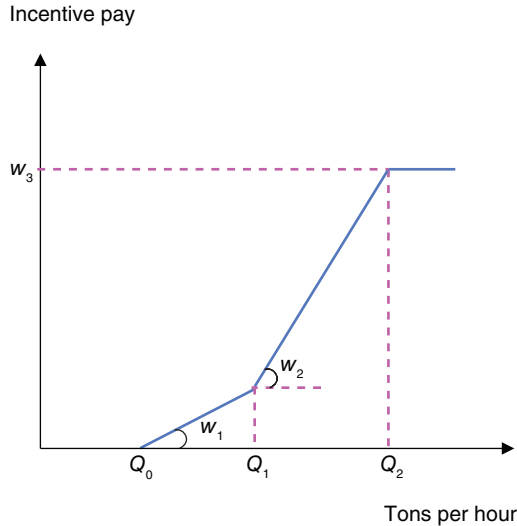


FIGURE 2. THE STEELMAKER'S INCENTIVE PLAN

Table 3 summarizes the parameters of the incentive scheme, the changes in these parameters, and the reasons for the changes. Notice that while the changes in the incentive scheme were induced by physical improvements, the adoption was lagged by several months, potentially allowing the separate identification of the impact of each event.

The actual incentive payments trended upward from around 35 percent of base salary in 2001, when the incentive scheme was just introduced, to around 60 percent toward the end of the sample period in 2008, although, as we show in the online Appendix, there is considerable variability around the trend. In the online Appendix we also report the percentage of the time that production reached the thresholds specified in Table 3. On average, production was above Q_0 about 94 percent of the time, above Q_1 about 78 percent of the time, and above Q_2 , about 17 percent of the time.

Finally, up to 2004, the melt shop operated the three daily shifts with 85 workers that were divided into three teams. As there was no reserve team, work load for the workers was very heavy (almost no vacations, and many overtime hours).

and the group itself pushed those week links out—we think because of our efficient incentive scheme.” Ghemawat (1994) discusses the effect of a similar incentive scheme at Nucor, which is a US mini mill operator and the largest steelmaker in the United States. He concludes that the most important effect of the incentive scheme “seems to have been to create peer pressure for individual workers to exert themselves for the good of the group.”

TABLE 3—THE INCENTIVE SCHEME

Date	Q_0	Q_1	Q_2	w_1	w_2	Event
June 1, 2001	18	20.5	24	20 percent	76 percent	New incentive model
March 1, 2003	19.75	22.25	25.25	17 percent	78 percent	EAF transformer
July 1, 2005	21.5	24.5	27.7	19 percent	79.8 percent	LF transformer

Starting from January 2004, the melt shop hired 18 new workers and introduced a fourth team to serve as backup. Following this change, the workers were organized in 4 teams of 26 workers each rotating to cover the three daily shifts.¹³

IV. Output Decomposition

We now look at the different elements of the output decomposition in (3). Figure 3 shows the monthly averages of plant utilization (actual plant hours divided by the total hours in a month), heats per effective day (the total number of heats in a given month divided by the number of effective days of operation during that month), and billets per heat during our sample period.

Figure 3 shows that plant utilization, which reflects the percentage of time during a given month in which the melt shop was up and running, increased gradually over the 1997–2001 period, from an average of 79.1 percent during 1997–1998, to 89.3 percent during 1999–2001, and then to 93.4 percent during 2002–2008. The standard deviation of plant utilization fell from about 10 percent in 1998 to around 3 percent from 2005 onward. Interviews with the steelmaker’s management reveal that the increase in plant utilization between 1997–2001 was achieved by reducing the downtimes needed for planned maintenance from one day a week in 1997 to about eight hours every two weeks, and by reducing the number and length of unexpected delays.¹⁴ The later was done in part by giving workers more freedom in deciding how to handle problems.¹⁵

Figure 3 also shows that the number of heats per effective day rose quite sharply, from a little over 15 heats per day at the beginning of 1997 to around 25 heats per day toward the end of the sample period. The increase is gradual and steady, but unlike plant utilization, it is apparent throughout most of the sample.

Finally, Figure 3 shows that billets per heat also rose sharply over the sample period from about 23 tons per heat, early in the sample, to well over 26 tons per heat by 2008. A gradual but steady increase is apparent from 2003 to 2008, with a possible jump in mid 2005.

¹³In order to compensate existing workers for the drop in their overtime hours, the melt shop increased the hourly tariff of all senior workers by 17 percent.

¹⁴For example, the furnace shell, which is made of steel, is lined with refractories (nonmetallic materials that can sustain high temperatures) to protect the shell from melting. Refractories need to be replaced periodically and this may cause delays. Moreover, due to wear, corrosion, and fatigue by either external damage or human error, the equipment in the melt shop has to go through periodic service maintenance, which require downtimes.

¹⁵Before the melt shop was acquired by the current owner, management was very centralized and workers tended to seek the CEO’s advice on how to deal with unexpected problems in the production process.

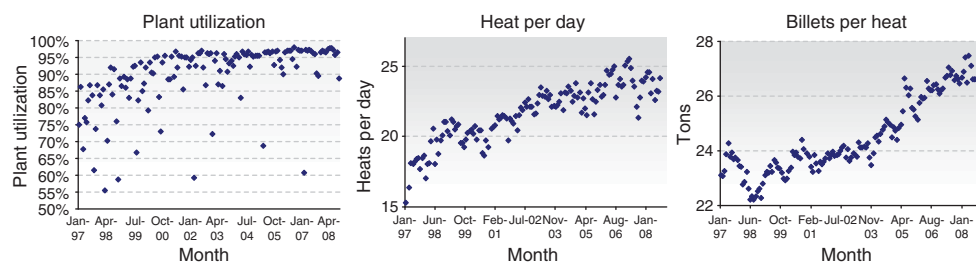


FIGURE 3. MONTHLY AVERAGES OF PLANT UTILIZATION (*actual plant hours divided by the total hours in a month*), HEATS PER DAY, AND BILLETS PER HEAT, JANUARY 1997–SEPTEMBER 2008

TABLE 4—TIME TRENDS, JANUARY 1997–SEPTEMBER 2008, MONTHLY DATA

Dependent variable	Billets per day		Plant utilization		Heats per day		Billets per heat	
	Coeff	<i>t</i> -stat	Coeff	<i>t</i> -stat	Coeff	<i>t</i> -stat	Coeff	<i>t</i> -stat
Trend	2.70***	11.10	0.002***	14.18	0.07***	5.61	0.01	1.22
Trend × 2001–2003	−0.94*	−1.79	−0.003***	−6.22	−0.02	−0.83	0.02*	1.66
Trend × 2004–2008	0.17	0.30	0.001	1.07	−0.03*	−1.69	0.02**	2.36
Constant	321.44***	10.04	0.80***	115.38	17.59***	33.75	23.11***	76.22
R^2	0.90		0.61		0.82		0.90	
Observations	128		128		128		128	

Note: *t*-statistics computed using the Newey-West standard errors with four lags.

To summarize the picture that emerges from Figures 1 and 3, we now regress our measure of output, billets per day, and its three components, on a time trend, using monthly data and allowing for breaks in the trend.

Table 4 shows that all four time series have a significant upward time trend at some point of the sample. During the January 1997–July 2001 period, the melt shop was producing, with each passing month, 2.70 more tons of billets per day, raised its utilization by 0.2 percent, and ran 0.07 more heats per day, while billets per heat were stable. The growth slowed down somewhat after 2001, mostly because of a slow down in the growth of plant utilization and heats per day. Interestingly, during the 2004–2008 period the overall trend remained stable; while billets per heat grew at a rate of 0.02 per month, heats per day slowed down.

V. Sources of Productivity Gains

We now relate the evolution of the billets per day output, y , and its three components, U , h , and y_h , to the events described in Sections IIIA and IIIB. The goal is to see which of the potential investments and labor related changes (establishing the “4th team” and changes in the incentive scheme) may be responsible for the productivity gains in total output and its three components.

Table 5 presents results for the period January 1997–June 2001, during which we only have monthly data, while Table 6 shows the sample with daily data, during the period July 2001–September 2008. The dummy variables associated with each event take the value 0 up to and including the relevant date, and take the value 1 from

TABLE 5—REGRESSION RESULTS, JANUARY 1997–JUNE 2001, MONTHLY DATA

Dependent variable	Billets per day		Plant utilization		Heats per day		Billets per heat	
	Coeff	<i>t</i> -stat	Coeff	<i>t</i> -stat	Coeff	<i>t</i> -stat	Coeff	<i>t</i> -stat
March 1997	42.10**	2.28	-0.019	-0.55	2.30***	5.89	0.57**	2.26
Sep. 1997	-24.83	-1.34	-0.022	-0.66	-0.32	-0.80	-0.45	-1.49
March 1998	-8.43	-0.55	-0.021	-0.59	0.99*	1.84	-0.94**	-1.98
Oct. 1998	24.42	1.20	0.004	0.09	0.71	1.30	0.53	1.18
Aug. 1999	-51.29***	-2.79	-0.046	-1.31	-1.50***	-3.27	0.07	0.17
Feb. 2000	3.63	0.27	-0.002	-0.08	-0.24	-0.50	0.50	1.41
Sep. 2000	17.06	-0.69	-0.032	-0.67	-0.16	-0.29	0.08	0.17
Incentive	-7.54	-0.81	-0.028	-1.55	0.48	1.17	-0.28	-1.05
Trend	4.10**	2.02	0.005	1.32	0.07	1.33	0.00	0.09
Constant	278.9***	40.18	0.799***	40.24	15.09***	178.66	23.24***	267.69
R^2	0.81		0.48		0.85		0.64	
Joint significance of dates	$F = 11.78***$		$F = 0.78$		$F = 58.77***$		$F = 11.52***$	
Observations	46		46		46		46	

Note: *t*-statistics computed using the Newey-West standard errors with 4 lags.

TABLE 6—REGRESSION RESULTS, JULY 2001–SEPTEMBER 2008, DAILY DATA

Dependent variable	Billets per day		Plant utilization		Heats per day		Billets per heat	
	Coeff	<i>t</i> -stat	Coeff	<i>t</i> -stat	Coeff	<i>t</i> -stat	Coeff	<i>t</i> -stat
March 17–27, 2002	30.61***	2.90	0.009	0.82	1.04**	2.57	-0.02	-0.18
Jan. 19–26, 2003	-6.17	-0.92	0.004	0.41	0.17	0.66	-0.26***	-2.62
Jun. 5–7, 2003	-2.39	-0.25	0.020	1.26	-0.37	-1.32	-0.10	-0.73
Apr. 19–22, 2004	22.94**	2.50	-0.004	-0.77	0.60**	2.05	0.37**	2.52
March 6–Apr 6, 2005	4.37	0.36	0.014**	2.45	-0.91**	-2.44	0.84***	3.14
Feb. 4–13, 2007	22.45	0.90	0.003	0.21	0.25	0.28	0.33*	1.87
Incentive 1	18.96***	4.16	-0.032**	-2.22	0.94***	6.38	0.18*	1.83
Incentive 2	33.82*	1.81	-0.015*	-1.75	1.62**	2.41	-0.01	-0.02
4th team	3.17	0.35	0.018**	2.30	-0.20	-0.74	0.17	1.24
Trend	0.01	0.27	0.000	0.35	0.00	-0.12	0.00**	2.25
Constant	468.41***	70.73	0.933***	131.3	20.92***	79.21	23.55***	312.84
R^2	0.19		0.00		0.14		0.75	
Joint significance of dates	$F = 2.87***$		$F = 4.55***$		$F = 6.09***$		$F = 8.46***$	
Joint significance of incentives	$F = 8.98***$		$F = 1.04$		$F = 20.4***$		$F = 1.7$	
Observations	2,558		2,570		2,528		2,528	

Note: *t*-statistics computed using the Newey-West standard errors with 4 lags.

the following date onward. For instance, the dummy March 17–27, 2002 takes the value 0 up to and including March 27, 2002, and takes the value 1 from March 28 onward.¹⁶ The Incentive dummy in Table 5 represents the introduction of a new incentive scheme on June 1, 2001, while the Incentive 1 and Incentive 2 dummies in Table 6 are associated with the two updates of the incentive scheme on March 1,

¹⁶The only exception is the March 6–April 6, 2005 dummy. Although the melt shop resumed operations on April 7, 2005, it returned to full capacity only on April 10, 2005. Hence, the dummy takes the value 0 up to April 9, 2005, and takes the value 1 only from April 10, 2005, onward.

2003 and July 1, 2005. The “4th team” dummy represents the introduction of a fourth team on January 1, 2004.¹⁷

Physical Investments.—Tables 5 and 6 show that some, but not all, of the dummy variables associated with potential physical investments are significant. For instance, the March 1997, March 17–27, 2002, and April 19–22, 2004 (the replacement of the EAF transformer) dummies all have a significant positive effect on billets per day, and all three dummies also have a significant positive effect on heats per day. In addition, the March 1997 and April 19–22, 2004 dummies also have a significant positive effect on billets per heat. The March 6–April 6, 2005 dummy (the replacement of the LF transformer) has a significant positive effect on plant utilization and billets per heat, but a significant negative effect on heats per day, so overall it does not have a significant effect on billets per day.¹⁸ Interestingly, the August 1999 dummy has a significant negative effect on billets per day and heats per day. Finally, the *F*-tests show that combined, the dummies associated with physical investments had a significant effect in both samples; the only exception is the plant utilization in Table 5, where the joint effect is not significant.

The Incentive Scheme.—Table 5 shows that the introduction of the incentive scheme in June 2001 had no significant effect on output, and if anything, it had a weakly significant negative effect on plant utilization. One may wonder if this result depends on the fact that the sample in Table 5 ends in June 2001, meaning that we only have one observation (June 2001) on the effect of the incentive scheme. We therefore rerun the monthly data regressions until the end of 2001, so that now we have seven observations following the introduction of the incentive scheme (June–December 2001). The results, however, do not change much and the incentive dummy remains insignificant in all four regression.

By contrast, Table 6 shows that the updates in the incentive scheme had a significant positive effect on output. This result is mainly due to the increase in heats per day. Indeed, the main purpose of the incentive scheme is to induce workers to work faster (i.e., induce workers to “run rather than walk” as management told us), which should boost the number of heats per day. Interestingly, the updates in the incentive scheme are associated with a decrease in plant utilization, especially after the first update on March 1, 2003 (the replacement of the EAF transformer). It is possible that faster operation leads to more equipment problems though we do not have direct evidence on that.

¹⁷The data on event months is omitted from the regressions in Table 5 since these months have unusually low output level (this is indeed how we identify them). The number of observations is not the same in all regressions in Table 5, due to some missing observations (e.g., we have more observations on billets per day than on plant hours or heats). We omitted from the billets per day, heats per day, and billets per heat regressions in Table 6 observations on days in which no production took place (these days were included in the plant utilization regression).

¹⁸The negative effect on the March 6–April 6, 2005 dummy on heats per day seems plausible since an increase in either k_{LF} or a_{LF} apparently enabled melting more scrap per heat, which is expected to take longer. Indeed, this event is associated with the main jump in scrap, gas, and oxygen per heat (and gas and oxygen per billet) during the sample, suggesting that more is melted, perhaps for a longer time.

The Fourth Team.—Table 6 shows that establishing a fourth team in January 2004 had a positive significant effect on plant utilization, which is reasonable given that the team’s main purpose was to serve as a backup. The fourth team, however, did not significantly affect billets per day, nor the other two components of output.

Time Trend.—While Table 4 shows a significant upward time trend in output and its three components, Tables 5 and 6 show that once we control for the different events, there is a significant upward time trend only in the billets per day regression in Table 5 and the billets per heat regression in Table 6.

Learning by Doing versus Tweaking.—Learning by doing refers to the beneficial effect of accumulated knowledge on productivity (Arrow 1962). Such knowledge is typically modeled as driven by accumulated past output (e.g., Benkard 2000, Thompson 2001). We now examine whether productivity gains are indeed associated with past accumulated output (irrespective of whether the firm experimented with different production techniques in order to learn how to tweak the production process).

To this end, we define experience—in logs—in period t as the accumulated output up to period $t - 1$:

$$e_t = \log \left(\sum_{\tau=1}^{t-1} y_\tau \right).$$

We regress monthly output y_t , on e_t , as well as on all the events reported in Tables 5 and 6. We use monthly data for the entire sample period, since it is unlikely that the melt shop can learn on a daily basis. Similarly, we define the logged experience of each of the three components of output (plant utilization, heats per day, and billets per heat) as follows:

$$e_t^c = \log \left(\sum_{\tau=1}^{t-1} c_\tau \right), \quad c_t = y_h, h_t, U_t,$$

and regress each of the three components, using monthly data on e_t^c , as well as on all the events.

Table 7 reports the results of the four regressions in logs, since that is the preferred specification in the literature, where log experience is used to explain log output. For the sake of brevity, we do not report the coefficients on the various events, as we are mainly interested here in the effect of experience on output and its components (the events are just used as controls). Since we do not have an experience variable for January 1997, and since March 1997 is an “event” month with unusually low output level, we start the regression in April 1997.

Logged experience per se does not help explain the overall growth in the melt shop’s output, nor the evolution of its three components. When the trend is removed, the coefficients of the experience variables become positive, as experience captures the omitted trend. However, under learning by doing, accumulated experience should explain more than a trend. Deviations from the trend in experience should be associated with above trend performance. It does not seem to be the case here.

TABLE 7—REGRESSION RESULTS ON THE EFFECT OF EXPERIENCE ON BILLETS PER DAY AND ITS DECOMPOSITION TO COMPONENTS, APRIL 1997–SEPTEMBER 2008, MONTHLY DATA

Dependent variable	Billets per day		Plant utilization		Heats per day		Billets per heat	
	Coeff	<i>t</i> -stat	Coeff	<i>t</i> -stat	Coeff	<i>t</i> -stat	Coeff	<i>t</i> -stat
Experience	0.23	0.47	−0.23	−0.32	0.13	0.31	0.18	0.89
Trend	−0.05	−0.08	0.43	0.49	−0.09	−0.17	−0.18	−0.72
Event dummies	Yes		Yes		Yes		Yes	
<i>R</i> ²	0.92		0.63		0.88		0.95	
Observations	126		126		126		126	

Note: *t*-statistics computed using the Newey-West standard errors with four lags.

TABLE 8—THE CHANGE IN OUTPUT COMPONENTS OVER THE SAMPLE PERIOD: JANUARY 1997–SEPTEMBER 2008, MONTHLY DATA

	<i>y</i>	<i>U</i>	<i>h</i>	<i>y_h</i>
Average value Jan. 1997–Dec. 1997	320.9	0.7839	17.3	23.60
Average value Jan. 2008–Sep. 2008	612.9	0.9603	23.7	26.88
Difference	292	0.1764	6.4	3.28
Difference in percentage terms	91 percent	22.5 percent	37 percent	13.9 percent

In sum, the evidence is consistent with the reports from management, that productivity gains were the outcome of trial and error, rather than simply a function of accumulated production.

VI. Decomposing Productivity Gains

We now use the estimated coefficients of the previous regressions to impute the productivity gains potentially associated with the various events. The coefficient of each dummy represents the gain at the time of the event. By adding all dummies, which we found significantly different from zero, we impute all the gains in productivity associated with the events described in Sections IIIA and IIIB. The remainder, or unexplained, output growth represents the productivity growth associated with other managerial activities.

Table 8 presents the change in plant utilization, *U*, heats per day, *h*, and billets per heat, *y_h*, over our sample period.

Substituting the numbers in Table 8 in (3), we can now decompose the overall increase in billets per day over the sample period as follows:

$$(4) \quad (1 + dU)(1 + dh)(1 + dy) = 1.225 \times 1.37 \times 1.139 = 1.91.$$

Let us first consider physical investments. The sum of the significant date dummies, those associated with potential plant shut downs for investments, represent a total decrease of 9.19 tons of billets per day (42.10 – 51.29) during the first period, and an increase of 53.54 tons of billets per day (30.61 + 22.94) during the second part of the sample. In total then, the date dummies can explain an increase of 44.36 tons of billets per day, out of the total increase of 292 tons of billets per day. This amounts to 15.2 percent of the total increase.

Looking at the different components in Tables 5 and 6, we see that the physical investments increased output primarily by increasing heats per day (the significant date dummies amount to 2.52 heats per day out of the total increase of 6.4) and billets per heat (the significant date dummies amount to 0.91 billets per heat out of the total increase of 3.28), while having only a small effect on plant utilization (the significant date dummies amount to 0.014 out of the total increase of 0.1764).

Second, the incentive scheme has a significant effect on billets per day only in Table 6, where combined, the two incentive dummies are associated with increases of 52.78 tons of billets per day ($18.96 + 33.82$), which amounts to 18.1 percent of the total increase of 292 tons in billet per day. Table 6 shows that the gains come mostly from the positive effect on heats per day (the significant incentive dummies amount to 2.56 heats per day out of the total increase of 6.4). The effect on billets per heat is small (the significant incentive dummies amount to 0.18 billets per heat out of the total increase of 3.28), while, surprisingly, the effect on plant utilization is negative (the significant incentive dummies amount to -0.047). Finally, the 4th team dummy only has a statistically significant effect on plant utilization.

In total, the explained components amount to 97.13 of daily output growth, which represent a third of the total increase of 292 tons of billets per day during the sample period.¹⁹ The remaining growth of 194.8 tons of billets per day ($292 - 97.13$), which is left unexplained by the investments and the incentive scheme, represents 66.7 percent of the total growth, and amounts to annual growth of 4.12 percent ($(1 + 194.8/320.9)^{1/11.67} - 1$).

Another way to measure productivity is to look at the evolution of value added instead of gross output. We define value added, at constant prices, as

$$VA = \bar{p}_y y - \sum_{i=1}^n \bar{p}_i x_i,$$

where y represents the output of billets, \bar{p}_y is the average price of billets over the sample period, x_1, \dots, x_n is a vector of material and energy inputs, including scrap, electricity, Ferro alloys, Oxygen, Propane, lime, Electrodes, and Carbon, and \bar{p}_i is the average price of input i over the sample period. We use constant prices in order to ensure that value added reflects changes of physical units, as opposed to changes in the relative prices of inputs and output. For instance, if billet prices increased more than input prices, value added would increase for reasons which are unrelated to productivity.

Since capital and labor were more or less constant over the sample period (save for the events), we can think of the growth in VA as a measure of the evolution of capital and labor productivity. Loosely speaking, TFP can be defined as $VA/(\bar{p}_k K + \bar{p}_L L)$, where $\bar{p}_k K$ and $\bar{p}_L L$ are the values of capital and labor inputs, measured in constant prices. In our case, both K and L were fixed over the sample period (up to the events), so the evolution of VA can be interpreted as a proxy for TFP.

¹⁹ Interestingly, if we also take into account all the jointly significant dummies (the investment dummies in the billets per day, heats per day, and billets per heat regressions in Table 5 and all the investments dummies in Table 6), we either get very similar, or even smaller, explained growth, because many of the dummies in Tables 5 and 6, which are jointly but not individually significant, have negative coefficients.

Value added increased from 1997 to 2008 by 63.7 percent. In the online Appendix, we report the results of a regression of *VA* on all the events, using monthly data. The results show that the events explain only 38.3 percent of the increase in *VA*. The remaining 61.7 percent remain unexplained. The unexplained growth in *VA* amounts to an annual productivity growth of 3.06 percent.

VII. Discussion and Conclusions

This study documents the evolution of productivity in a firm operating 24/7 in a traditional, mature, industry. Despite the absence of dramatic changes in the plant itself or the workforce, output increases gradually and continuously throughout the sample period. While an incentive scheme and some investments explain part of the gains in the different components of output, we are left with most of the gain unexplained. This gain is also not explained by cumulative experience, as one would expect based on standard learning-by-doing models. Moreover, the gain cannot be explained by R&D as the firm we study uses standard equipment that cannot be modified by the firm itself.²⁰

Learning by experimenting, or “tweaking the production process,” is the best explanation we gather from conversations with management. As it turns out, steel production in mini mills involves numerous trade-offs. For instance, using more refractories (nonmetallic materials that line the EAF’s shell and protect it from melting) allows the melt shop to run more heats before the refractories need to be replaced, but at the same time, it limits the amount of scrap that can be charged into the EAF, and hence the quantity of billets per heat. Likewise, using a longer electric arc allows the melt shop to reach higher temperatures inside the EAF and thereby speeds up the heat cycles, but may damage the refractories and requires the melt shop to replace them sooner (replacing the refractories requires a downtime). As a third example, charging more scrap into the EAF, increases the quantity of billets per heat, but can also raise the probability that the electrodes (that strike the electric arc inside the EAF) will break, in which case the melting process needs to be stopped until the electrodes are replaced. Finding the optimal balance between the various trade-offs requires a lengthy trial and error process that can be very slow, given that there are many variables that may affect the various trade-offs. Moreover, these variables differ across melt shops, even if they are all using the same equipment. The implication is that “learning how to use the melt shop optimally,” or “tweaking the production process” is a slow process that involves numerous trade-offs and can take a long time.

Beyond their theoretical and empirical relevance, our findings imply that learning by doing is not simply a function of cumulative output and is not guaranteed automatically. Rather, it is the result of an active experimentation process. Of course, our results reflect the learning process at one particular plant, in one particular industry. In this sense, our study shares the issue of generalizability with most of the rest of the learning-by-doing literature. Nevertheless, we believe that the findings offer insights that can be cautiously extended to other production operations, particularly complex manufacturing processes.

²⁰In an interview, the steelmaker’s CEO said “in the steel industry you cannot invent anything. You must use the equipment according to the manufacturer’s specifications.” Interestingly, when early on the steelmaker tried to improve on the way baskets of scrap are charged into the EAF, the experiment has ended in an accident.

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