Reallocation and Technology: Evidence from the U.S. Steel Industry *

Allan Collard-Wexler and Jan De Loecker
NYU and NBER, and Princeton University, NBER and CEPR

December 19, 2013

Abstract

We measure the impact of a drastic new technology for producing steel – the minimill – on the aggregate productivity of U.S. steel producers, using unique plant-level data between 1963 and 2002. We find that the sharp increase in the industry's productivity is linked to this new technology through two distinct mechanisms. First, minimills displaced the older technology, called vertically integrated production, and this reallocation of output was responsible for a third of the increase in the industry's productivity. Second, increased competition, due to the expansion of minimills, drove a substantial reallocation process *within* the group of vertically integrated producers, driving a resurgence in their productivity and, consequently, the productivity of the industry as a whole.

Keywords: Productivity; Technology; Competition; Reallocation.

*We would like to thank Jun Wen for excellent research assistance, and Jonathan Fisher for conversations and help with Census Data. We would like to thank the co-Editor (Luigi Pistaferri) and three anonymous referees for excellent comments and suggestions. Furthermore, we thank Nick Bloom, Rob Clark, Liran Einav, Ariel Pakes, Kathryn Shaw, Chad Syverson, Raluca Dragusanu, and seminar participants at many institutions. This paper uses restricted data that were analyzed at the U.S. Census Bureau Research Data Center in New York City. Any opinions and conclusions expressed herein are those of the authors and do not necessarily represent the views of the U.S. Census Bureau. All results have been reviewed to ensure that no confidential information is disclosed. Contact details: Allan Collard-Wexler, wexler@nyu.edu; and Jan De Loecker, jdeloeck@princeton.edu. The usual caveat applies.

1 Introduction

Identifying the sources of productivity growth of firms, industries, and countries, has been a central question for economic research. There remain, however, many empirical obstacles to credibly identifying the underlying sources of productivity growth. First, the measurement of productivity at the producer level typically requires an estimate of the production function and, therefore, has to confront both the endogeneity of inputs and unobserved prices for inputs and outputs. Second, it is difficult to observe potential explanatory variables at the producer level, such as technology, competition, and management practices.[1] Finally, in order to establish causality, exogenous shifters of such variables are required in order to trace out their effects on productivity.

A recent literature has emphasized the distinction between the productivity effects that occur at the producer level, and those realized by moving resources between producers – i.e., the reallocation mechanism. Although it is now well established, at both a theoretical and empirical level, that the reallocation of resources across producers is important in explaining aggregate outcomes, it has been very hard to identify the exact mechanisms behind it.[2] In this paper, we focus on the role of technology and the associated changes in competition in driving the reallocation process underlying aggregate productivity growth.

We examine one particular industry, the U.S. steel sector, for which we have detailed producer-level production and price data. Our setting is well suited to measuring the role of technological change, since we directly observe the exogenous arrival of a new production process – the minimill – at the plant level. In addition, we observe detailed output and input data, including physical measures of inputs and outputs, as well as standard revenue and expenditure data, to obtain measures of productivity and market power. These inputs and outputs are remarkably unchanging over a 40-year period, and the steel products shipped in the 1960s are very similar to those shipped in 2002. Thus, productivity growth in steel is almost uniquely driven by process innovation, rather than through the introduction of new goods. Observing a panel of steel producers over a 40-year period, 1963-2002, allows us to study the long-run implications of increased competition, such as the slow entry and exit process.

The U.S. steel industry shed about 75 percent of its workforce between 1962 and 2005, or about 400,000 employees. This dramatic fall in employment has far-reaching economic and social implications. For example, between 1950 and 2000, Pittsburgh – which used to be the center of the U.S. Steel Industry – dropped from the tenth-largest city in the United States to the 52nd largest.

While employment in the steel sector fell by a factor of five, shipments of steel products in 2005

[1] See Syverson (2011) for an excellent overview of the various potential determinants of productivity at both the producer and the industry level. Two prominent studies on the triggers of productivity growth are Schmitz (2005) and Olley and Pakes (1996), who study the role of two such triggers: import competition in the iron ore market and deregulation in the telecommunications market. Hortaçsu and Syverson (2004), Bloom et al. (2013), and Jarmin et al. (2009) show that factors such as vertical integration, management, and large retail chains lead to systematic differences in productivity between plants and consequently, have implications for aggregate industry performance.

[2] For instance, Melitz (2003), shows how trade liberalization impacts aggregate productivity through a reallocation towards more-productive firms, while Foster et al. (2001) and Bartelsman et al. (2009) document the role of reallocation empirically.

reached the level of the early 1960s. Thus, output per worker grew by a factor of five, while total factor productivity (TFP) increased by 38 percent. This makes the steel sector one of the fastest growing of the manufacturing industries over the last three decades, behind only the computer software and equipment industries. We highlight the special features of the U.S. steel industry in Table 1, where we report its change in output, input use, TFP and prices over the period 1972-2002 and compare it to the mean and median manufacturing sector's experience.

Table 1 points out the unique feature of the steel industry: The period of impressive productivity growth – 28 percent compared to the median of three percent – occurred while the sector contracted by 35 percent. The starkest difference is the drop in employment of 80 percent compared to a decline of five percent for the average sector.

We find that the main reason for the rapid productivity growth and the associated decline in employment is neither a steady drop in steel consumption nor the emergence of globalization. Nor is it a displacement of production away from the midwest. The increase in productivity can be directly linked to the introduction of a new production technology, the steel *minimill*. The minimill displaced the older technology, called vertically integrated production, and this reallocation of output was responsible for about a third of the increase in the industry's total factor productivity. In addition, minimills' productivity steadily increased. We can directly attribute almost half of the aggregate productivity growth in steel to the entry of this new technology.

However, the older technology was not entirely displaced. Instead, vertically integrated producers experienced a dramatic resurgence of productivity and, by 2002, were on average, as productive as minimills. This resurgence was not driven by improvements at integrated plants. Rather, less-productive vertically integrated plants were driven out of the industry, and output was reallocated to more-efficient producers. We see exit of vertically integrated producers in precisely the product segments where they competed head-to-head with minimills.

When we evaluate the impact of a drastic technological change on aggregate productivity growth, we also control for other potential drivers of productivity growth, including international competition, geography, and firm-level factors such as organization and management. We also show that markups in this industry fell by 50 percent over the last 40-years, which is not surprising if we look at the output and input price changes in Table 1. This increase in productivity, and fall in markups, jointly lead to a predicted increase in consumer surplus of between nine and 11 billion dollars per year.

In addition to identifying the exact mechanisms underlying productivity growth, which are of interest to a growing literature on reallocation and productivity dispersion, the steel industry is also important in and of itself. Even today, it is one of the largest sectors in U.S. manufacturing: In 2007, steel plants had shipments of over 100 billion dollars, of which half was value added. Therefore, understanding the sources of productivity growth in this industry is of independent interest.

The remainder of the paper is organized as follows. Section 2 describes the data. In Section 3, we present five key facts that help guide the empirical analysis, which we take up in Sections 4 and 5. We discuss alternative specifications and robustness in Section 6 and conclude in Section 7.

2 Data

We study the production of steel: plants engaged in the production of either carbon or alloy steels. We rely on detailed Census micro data to investigate the mechanisms underlying the impressive productivity growth in the U.S. steel sector. Our analysis is based on plant-level production data of U.S. steel mills from 1963 to 2002.

We use data provided by the Center for Economics Studies at the United States Census Bureau. Our primary sources are the Census of Manufacturers (CMF), the Annual Survey of Manufacturers (ASM), and the Longitudinal Business Database (LBD). We select plants engaged in the production of steel, coded in either NAICS (North American Industrial Classification) code 33111, or SIC (Standard Industrial Classification) code 3312. The CMF is sent to all steel mills every five years, while the ASM is sent to about 50 percent of plants in non-Census years. However, the ASM samples all plants with over 250 employees and, encompasses over 90 percent of the steel sector's output.

In addition, we collect data on the products produced at each plant using the product trailer to the CMF and the ASM, and we collect the materials consumed by these plants from the material trailer to the CMF.

We rely on our detailed micro data to divide steel mills into two technologies: Minimills (MM, hereafter) and Vertically Integrated (VI, hereafter) Producers. VI production takes place in two steps. The first stage takes place in a blast furnace, which combines coke, iron ore, and limestone to produce pig iron and slag. In the second stage, the pig iron, along with oxygen and fuel, is then used in a basic oxygen furnace (BOF) to produce steel.[3] The steel products produced in either MM or VI plants are shaped into sheets, bars, wire, and tube in rolling mills. These rolling mills are frequently collocated with steel mills, but can also be freestanding units.

In contrast, MMs are identified primarily by the use of an electric arc furnace (EAF) to melt down a combination of scrap steel and direct reduced iron.[4] Because these mills have a far smaller efficient scale, they are, on average, an order of magnitude smaller than vertically integrated producers. Historically, EAFs were used to produce lower-quality steel, such as that used to make steel bars, while virtually all steel sheet (needing higher-quality steel) was produced in BOFs. However, since the mid-1980s, innovation in the EAFs has enabled them to produce certain types of sheet products, as well.[5]

We classify plants as minimills, vertically integrated plants, and rolling mills using their responses

[3]There were a few open-hearth furnaces in operation during the sample period. However, as of the late 1960s, open-hearth plants accounted for only a very small portion of output, and the last open-hearth plant closed in 1991. See Oster (1982) for more on the diffusion of BOF mills.

[4]The median scrap vintage is quite old, as one would expect, with items such as rails, construction rebar, and other white goods accounting for a large share of scrap. Moreover, in the United States, there is an abundant supply of scrap. Indeed, the largest steel export from the United States, by quite a margin, is steel scrap destined for minimills in China and Japan. It is also possible to produce steel in a minimill without scrap: Direct Reduced Iron (DRI) is a substitute for scrap. Typically, the prices for DRI have been higher than for scrap, but minimills could also exist in a world without vertically integrated production of steel. There was a worry in the industry during the 1970s that scrap would become scarce, and, thus, some direct reduced iron facilities were built. See Chapter 5, page 95, in Barnett and Crandall (1986) for a discussion.

[5]EAFs have a long history in steel making. However, before the 1960s, they primarily produced specialty steels.

to a specific questionnaire on steel mills attached to the 1992, 1997, and 2002 CMF. For prior years, we use the material and products produced by each plant to identify MM and VI plants. More detail on the classification of plants can be found in Appendix A. Table B.1 shows summary statistics for the sample of MM and VI plants. The average VI plant had shipments of 647 million dollars, of which 47 percent is value added, while the average MM plant shipped 153 million dollars, of which 44 percent is value added, where all dollar amounts are in 1997 $.

3 Key Facts in the U.S. Steel Sector 1963-2002

In this section, we briefly go over some key facts of the U.S. steel sector. These facts will be important to keep in mind when we analyze the sources of productivity growth.

3.1 Stagnant Shipments, Rising Productivity

From Table 1, we know that the productivity growth in the U.S. steel sector was one of the fastest in manufacturing. To better understand this period of impressive productivity growth, we plot total output next to labor and capital use in Figure 1. An important observation is that the period of productivity growth came about while the industry as a whole contracted severely: Steel producers sold about 60 billion dollars in 1960 and, reached 100 billion dollars in shipments by the early 1970s. A decade later, only 40 billion dollars of production was shipped, or, put differently, the sector's shipments decreased by more than half.

Total employment, on the other hand, decreased consistently, even during the recovery of output in the late 1980s and throughout the 1990s. The employment panel of Figure 1 shows that total employment fell from 500,000 to 100,000 employees – one of the sharpest drops in employment experienced by any sector in the U.S. economy. By 2000, the steel industry employed a fifth of the number of workers that it had in 1960, while production of steel went from 130 million tons in 1960 to 110 million tons in 2000. This implies that output per worker increased from 260 to 1100 tons.[6] Total material use tracks output quite closely, while labor and capital fell continuously over the entire period, which suggests that TFP had to increase to offset the sharp drop in labor and capital.[7]

3.2 A New Production Technology: Minimills

The entry of minimills in steel production constituted a drastic change in the actual production process of steel products. A natural question to ask is whether MM are any different than the traditional VI steel producers. We rely on a descriptive OLS regression, where we regress various plant characteristics on

[6] Shipments of steel in tons are collected from various Iron and Steel Institute Annual Statistical Reports (American Iron and Steel Institute, 2010).

[7] For this aggregate analysis, we rely on the NBER's five-factor TFP estimate. See Bartelsman et al. (2000) for more detail.

an indicator variable for whether a plant is a vertically integrated producer. We consider a log specification such that the coefficient on the technology dummy directly measures the percentage *premium* of VI plants.

Table B.2 lists the set of estimated coefficients, and confirms that vertically integrated producers are, on average, four times bigger, as measured by the large coefficients on shipments, value added, and inputs. For example, VI plants, on average, ship 144 percent more than MMs. Moreover, VI producers generate about 20 percent more shipments per worker, which suggests that they are more productive. However, when we combine the coefficients on all three inputs (labor, materials and capital) with the shipment premium, we see that total factor productivity (TFP) of MM is at least as high as that of VI producers. We conduct a more precise comparison of TFP across technologies in Section 4.

In addition to the average premium over the entire sample, we report time-specific coefficients. Across all the various characteristics, the VI coefficient falls over time. Most notably, shipments per worker were 23-percent higher for VI plants in 1963, but by 2002, there was no significant difference between the two technologies in terms of labor productivity. This pattern suggests that, over time, VI and MM producers became more alike, although VI producers still produce on a larger scale.

The coefficients on wages of six percent, shown in the last row of Table B.2, confirms the well-known fact that VI producers, on average, pay higher wages. This is likely due to the impact of unionization – minimill workers typically being non-unionized.[8] It is interesting to note that this average difference in wages of six percent would only translate into a difference in costs of only 1.2 percent given the input share of labor for steel producers.

We also find large differences in standard measures of performance, such as profit margins, defined as sales minus cost of materials and salaries over sales, and the rate of return on capital, defined as sales minus cost of materials and salaries over capital. Table B.4 considers quantile regressions of either the profit margin or the rate of return on capital on an indicator for whether or not a plant is vertically integrated, along with a full set of year fixed-effects. We find that minimills have a rate of return on capital that is 18-percent higher than for vertically integrated plants. In addition, minimills have a profit margin that is four-percent higher than that of vertically integrated plants. Minimills are less capital-intensive than vertically integrated plants, and this explains some of the discrepancy between these measures of profitability.

An important difference between MM and VI producers is the set of products they manufacture. Figure 2 shows that in 1997, MMs accounted for 59 percent and 68 percent of shipments of steel ingots and hot-rolled bar respectively, but only 15 percent and 14 percent of hot and cold rolled sheet. MMs typically produce lower-quality steel products, which are generally thicker products, while VI plants produce higher-quality products, which are usually sheet products. However, the product mix accounted for by MMs changed dramatically over the last 40 years. Figure 2 shows that, in 1977, MMs produced 27 percent of steel ingots and 24 percent of hot-rolled bar. Between 1977 and 1982, MMs

[8]See Hoerr (1988) – and in particular, page 16 – for evidence of the role of unionization on wages for VI and MM producers. We discuss the role of unions in more detail in Section 4.2

increased their share of both of these products to 40 percent, and by 2002, they produced 81 percent of hot-rolled bar. As stated above, in 1997, only 15 percent and 14 percent of hot and cold rolled sheet were produced by MMs.[9] Thus, the market share of MMs in the higher-quality product segments, sheet products, was rather stable up to 1997, after which their market shares increased substantially.

3.3 A Stable Product Mix over Time

We list the product mix of the steel industry in Table B.3. We break down steel into various products: a) hot-rolled steel sheet (HRS); b) hot-rolled bar (HRB); c) cold-rolled sheet (CRS); d) ingots and shapes; e) pipe and tube (P&T); f) Wire g) cold-finished bars (CFB); and h) coke oven and blast furnace products (Blast). Over 40 years, the product mix for steel has barely changed. Hot-rolled sheet accounted for 23 percent of shipments in 1963 and 31 percent in 2002, and hot-rolled bar accounted for 23 percent of shipments in 1963 and 22 percent in 2002.

The fact that the steel industry's products have been unchanged is essential for our identification of productivity growth, as the industry's production process has changed far more than its products.

3.4 Heterogeneous Price Trends Across Products

While steel producers' product mix has been relatively unchanged from 1963 to today, the prices for these products have dropped considerably, which is not surprising given the large increases in TFP in the industry. Panel A of Figure 3 presents the price indices for the four main products – hot and cold rolled sheet, hot rolled bar and steel ingots – which, taken together, represent 80 percent of shipments in 1997.[10]

The same panel shows that the prices of all steel products followed a very similar, and gradually increasing, pattern up to 1980. But from 1982 to 2000, we see 50-percent drop in the real price of steel. This implies that, while shipments of steel in dollars dropped since 1980, the quantity shipped has gradually increased since the mid-1980s (see Panel 1 of Figure 1).[11]

In addition, when we decompose these price trends further, we find that the prices of hot-rolled bars and steel ingots have fallen faster than the prices of hot and cold rolled sheet. While sheet steel is produced primarily by VI producers, prices for bar and ingot products fell by ten percent more than those for sheet products in 1982-1984. This occurred precisely at the point at which MMs saw an increase in their market share of bar and ingot products.

Turning to prices for *inputs*, we construct an intermediate input price index P_{nt} for each intermediate input n, where $n = \{$Fuels, Electricity, Coal for Coke, Iron Ore, and Scrap Steel$\}$, using either the NBER fuel price deflator, or reported quantities and costs in the material trailer to the CMF (which

[9]Giarratani et al. (2007) discuss the entry of Minimills into the production of sheet products around 1990.

[10]We have taken care to deflate these price indices by the GDP deflator to show price trends for steel relative to the rest of the economy.

[11]Annual reports of the American Iron and Steel Institute (2010), where total tons of steel are recorded annually, indicate that quantity produced increased by about 30 percent between 1982 and 2002.

allow us to back out prices). We construct a plant-specific input price index (P_{it}^{M}) using a weighted average of these intermediate input-specific prices, P_{nt}, where the weights are the share of an intermediate n in total intermediate input use.[12]

We present the time series pattern of our constructed input price index in Panel B of Figure 3. We compare the publicly available NBER Material Price Index (NBER MPI) with our constructed input price index. We compute the mean of the latter by technology and find that the NBER MPI follows our price index closely. However, the aggregate input price index hides the heterogeneity in input prices, especially during the energy price spike in the late 1970s and early 1980s. While input prices were very similar around 1972, by 1982, integrated producers faced almost 20-percent-higher input prices, primarily because they purchased more energy-intensive inputs.

Therefore, in order to correctly identify the productivity effect of the arrival of the minimills, and their associated increased competition, it will be imperative to control for price differences, for both inputs and outputs, across plants and time.

3.5 Simultaneous Entry and Exit

From Figure 1, we know that the number of plants increased over time. In Table 2, we go a step further, showing both the number of MM and VI plants that entered or exited, as well as the market share these plants represent. There was marked entry of new plants in the early 1980s, a period during which the industry as a whole severely contracted.

The market share of plants entering from 1982 to 1992 was 20 percent, versus five percent in the previous two decades, while the market share of exiters was 18 percent during this period. Most entry in this period was due to minimills, and most exit was from vertically integrated producers.[13] From these entry and exit statistics, we expect an important role for entry and exit in explaining productivity growth.

4 Drivers of productivity growth

The previous section highlighted the difference in performance between MM and VI producers, and suggested a large potential role for reallocation across these technologies in explaining productivity growth. This paper is concerned with studying the productivity differences in detail and verifying the extent to which the entry of minimills contributed to the stark aggregate productivity growth in the industry. We proceed in two steps. First, we present our empirical framework used to estimate the production function and establish the productivity premium of minimills. Second, we verify the robustness of this premium by considering alternative drivers of productivity growth.

[12] Appendix C describes the construction of the input price index in detail.

[13] This phenomenon, the speeding up of exit and entry during a downturn, has been documented by Bresnahan and Raff (1991) for the motor vehicles industry during the Great Depression.

4.1 Productivity Differences Across Technology

Denote each technology – either MM or VI – as $\psi \in \{VI, MM\}$.[14] A plant i at time t can produce output Q_{ijt} of a given product j, using a technology ψ specific production technology:

$$Q_{ijt} = F_{\psi,t}(L_{ijt}, M_{ijt}, K_{ijt}) \exp(\omega_{it}). \tag{1}$$

Our notation highlights that VI and MM producers rely on different technologies, which we allow to vary over time. As is common in the literature, productivity ω_{it} is modeled as a Hicks-neutral term. Moreover, we assume that productivity is plant-specific.

4.1.1 Measurement

Recovering productivity using revenue and expenditure data requires that we correct for potential price variation across plants and time, for both output and inputs. Below, we describe our procedure briefly, and Appendix C provides more details.

In order to recover productivity, ω_{it}, using product-level revenue data for each plant, we assume that each product j is homogeneous, and we construct a plant-specific output price (P_{it}) using product-level BLS price data and then match that in with our production data.[15]

The bulk of quality variation operates across across product codes, particularly when it comes to comparing bar products to sheet products – perhaps the most obvious quality metric being how thick the steel product is, which determines the value for downstream users such as car producers and the construction industry. Our measures of productivity are designed to control for quality differences that materialize through price differences and allow for the comparison of plant-level productivity across producers of different product mixes. Of course, to the extent that there are quality differences across plants within our narrowly defined products – for example, Hot Rolled Bars broken into low-quality rebar used for reinforcing concrete versus higher-quality structural steel used to make frames for buildings – our measure of productivity will pick up these differences in quality as differences in output.[16] The working assumption is, thus, that the main quality differences exist among the nine product codes, and that the variation within products across plants comes from the cost side – i.e., through productivity differences.

We follow the literature and consider a Cobb-Douglas specification by type, which gives rise to the

[14] In the steel industry, a plant cannot switch technology, such as a VI plant becoming a MM. This is in contrast to the a setting of technology adoption, such as Van Biesebroeck (2003)'s empirical analysis of technology adoption in U.S. car manufacturing.

[15] We constructed nine product categories, which correspond to 7-digit NAICS codes, which are the most detailed plant level production statistics we have access to at Census.

[16] This is a standard problem in the literature, and with the exception of a few papers, such as De Loecker (2011); De Loecker et al. (2012), the norm is not to have any control for quality, let alone within a narrowly defined product category.

following expression for product-level sales by plant (for each type[17]):

$$R_{ijt} = L_{ijt}^{\beta_l} M_{ijt}^{\beta_m} K_{ijt}^{\beta_k} \exp(\omega_{it}) P_{jt}. \tag{2}$$

We are interested in recovering a measure of productivity at the plant level, and, therefore, aggregate up to plant-level sales. However, a common restriction in these type of data is that we do not directly observe the input use by product (see Foster et al. (2008)). We allocate inputs across products using product-specific sales shares, $s_{ijt}^R = \frac{R_{ijt}}{R_{it}}$, such that $X_{ijt} \equiv s_{ijt}^R X_{it}$ with $X = \{L, M, K\}$.[18] After aggregating (2) to the plant level, we obtain[19]:

$$\frac{R_{it}}{\sum_j s_{ijt}^R P_{jt}} = L_{it}^{\beta_l} M_{it}^{\beta_m} K_{it}^{\beta_k} \exp(\omega_{it}). \tag{3}$$

Although the focus in the literature has been mainly on the heterogeneity of output prices, input price variation potentially plagues the measurement of productivity, as well. The data on intermediate input use, M_{it}, are potentially the most contaminated by input price variation, both in the time-series and in the cross-section, particularly between MM and VI plants. The two technologies use vastly different intermediate inputs or use inputs at very different intensities, and, therefore, we expect the relevant input price to vary substantially across plants of different technologies.[20]

We construct our input price deflators in a similar way as the output price deflator. First, we need to distinguish between our three main input categories: labor, intermediate inputs and capital. We directly observe labor L_{it}: hours worked at the plant-level. For capital, we rely on the NBER capital deflator (P_t^K) to correct the capital stock series. For materials, we use our plant-level input price deflator P_{it}^M.

We estimate the production function using our constructed output and input price deflators, by type, using:

$$\tilde{q}_{it} = \beta_l l_{it} + \beta_m m_{it} + \beta_k k_{it} + \omega_{it} + \epsilon_{it}, \tag{4}$$

where lower cases indicate logs of deflated variables when appropriate.[21] We allow for unanticipated shocks to production and measurement error in output and prices, as captured by ϵ_{it}.[22] In the next subsection, we discuss the estimation and identification of equation (4).

[17] We drop the type subscript ψ and, unless stated otherwise, consider technology-specific production functions.

[18] As discussed in detail in Appendix C, this implies that we implicitly restrict markups to be common across products within a plant. We are not interested in explaining within-plant markup differences across products, but mainly aim to recover measures of plant-level productivity that are not contaminated by price variation across plants and time.

[19] Formally, this restricts the attention to constant returns to scale. First, we find strong evidence for constant returns to scale in our data. Second, our approach would only be modified by the inclusion of an additional term $\sum_j (s_{ijt}^R)^\gamma P_{jt}$ in the estimating equation, with $\gamma = \beta_l + \beta_m + \beta_k$.

[20] See Appendix C.2.2 for more detail on this point.

[21] E.g., $\tilde{q}_{it} = \ln\left(\frac{R_{it}}{\sum_j s_{ijt} P_{jt}}\right)$ and $m_{it} = \ln\left(\sum_n \frac{M_{int}^E}{P_{nt}}\right)$.

[22] Formally, the inclusion of ϵ_{it} is compatible with the existence of measurement error and unanticipated shocks in both revenue and price data. E.g., we observe revenue in the data and it relates to a firm's measure as follows: $R_{it} = R_{it}^* \exp(\epsilon_{it})$. Thus, the error term ϵ_{it} captures, potentially, multiple iid error terms. The distinction is not important for our analysis.

4.1.2 Estimation of production functions

We take equation (4) to the data and rely on a plant's optimal investment to control for unobserved productivity shocks. We estimate the production function rather than impute the production function coefficients from first-order conditions (FOC). This FOC approach infers production function coefficients from input revenue shares, where the coefficient on labor, for example, is simply given by the wage bill over sales. This approach requires that all inputs are fully flexible, which seems implausible in the steel industry given the irreversibility of capital investments and union labor contracts. As well, both output and input markets must be perfectly competitive for the FOC approach to be valid.

Our setting is very closely related to that of Olley and Pakes (1996), who use U.S. Census plant-level data on telecommunication equipment producers. While they are interested in a sales-generating production function, they are concerned that unobserved productivity shocks ω_{it} will bias the production function coefficients. This will lead to incorrect measures of productivity, and, thus, of any subsequent analysis of reallocation. To deal with the correlation between inputs and productivity (the simultaneity bias), and the non-random exit of plants (the selection bias), the authors rely on a plant's optimal investment equation to control for unobserved productivity shocks. We modify their approach and include the technology indicator, ψ_i, as a state variable in the firm's underlying dynamic problem.[23]

The firm's state is $s_{it} \equiv \{k_{it}, \omega_{it}, \psi_i\}$, and its investment policy function is, therefore, given by:

$$i_{it} = i_t(k_{it}, \omega_{it}, \psi_i). \tag{5}$$

Following Olley and Pakes (1996), we invert the investment function to obtain a control function for productivity: $\omega_{it} = h_{\psi,t}(k_{it}, i_{it})$.[24] We consider a first stage in which we relate output $\tilde{q}_{it}$ to a flexible function of inputs (l_{it}, m_{it}, k_{it}), investment, the technology dummy and year controls:

$$\tilde{q}_{it} = \phi_{\psi,t}(l_{it}, m_{it}, k_{it}, i_{it}) + \epsilon_{it}. \tag{6}$$

This first stage serves to purge measurement error and unanticipated shocks to production (ϵ_{it}) form the variation in output. Consequently, after this first stage, we know productivity up to the vector of (unknown) production function coefficients $\boldsymbol{\beta}$: $\omega_{it}(\boldsymbol{\beta}) \equiv \hat{\phi}_{it} - \beta_l l_{it} - \beta_m m_{it} - \beta_k k_{it}$.

A key component in the estimation routine is the law of motion on productivity that describes how a plant's productivity changes over time. The preliminary analysis indicates that exit, primarily by integrated mills, was substantial. We allow plant survival to depend on the plant's state variables,

[23] Plants never switch technologies. Therefore, we simply index all policy functions by ψ to allow the different technologies to face different demand or competitive conditions. In our main specification, we pool both technologies, and, therefore, indexing the policy functions by the technology is crucial. The pooling across all plants is useful, as we obtain one constant term, and can compare productivity levels across plants of different technologies.

[24] Note that the inclusion of extra fixed and observed state variables does not affect the invertibility – which covers exactly the case of our technology dummy. In addition, almost no plants report zero investment in a given year, so we can compute the control function for almost all plants in the sample. Plugging this control function into equation (4) would, in principle, allow us to identify the coefficients on variable inputs. However, we forgo identifying these coefficients in a first stage in order to relax the – by and large untestable – timing assumptions (see Ackerberg et al. (2007)).

which, in our case, include the technology dummy in addition to productivity, and capital. Following Olley and Pakes (1996), we rely on a nonparametric estimate of the plant's survival at time t, given the information set at time $t-1$, $\mathcal{I}_{t-1}$.

Define an indicator function χ_{it} to be equal to one if the firm remains active, and zero if it exits, and let $\underline{\omega}_{it} = \underline{\omega}_t(k_{it}, \psi_i)$ be the productivity threshold a firm has to clear in order to survive. The selection rule can be rewritten as:

$$\begin{aligned}
\Pr(\chi_{it} = 1) &= \Pr\left[\omega_{it} \geq \underline{\omega}_t(k_{it}, \psi_i) | \mathcal{I}_{it-1}\right] \\
&= \Pr\left[\omega_{it} \geq \underline{\omega}_t(k_{it}, \psi_i) | \underline{\omega}_t(k_{it}, \psi_i), \omega_{it-1}\right] \\
&= \rho_{t-1}(\underline{\omega}_t(k_{it}, \psi_i), \omega_{it-1}) = \rho_{t-1}(\underline{\omega}_t(\delta k_{it-1} + i_{it-1}, \psi_i), \omega_{it-1}) \\
&= \rho_{t-1}(k_{it-1}, i_{it-1}, \psi_i, \omega_{it-1}) \\
&= \rho_{t-1}(k_{it-1}, i_{it-1}, \psi_i) \equiv \mathcal{P}_{it}.
\end{aligned} \tag{7}$$

We use the fact that the threshold at t is predicted using the firm's state variables at $t-1$. As in Olley and Pakes (1996), we have two different indexes of firm heterogeneity: productivity and the productivity cutoff. Note that $\mathcal{P}_{it} = \rho_{t-1}(\omega_{it-1}, \underline{\omega}_{it}, \psi_i)$, and, therefore, $\underline{\omega}_{it} = \rho_{t-1}^{-1}(\omega_{it-1}, \psi_i, \mathcal{P}_{it})$.

To the extent that vertically integrated plants are larger and, thus, more likely to remain in the industry, this will generate different exit policies for minimills and vertically integrated plants. This survival probability is identified off the timing assumption, just as in Olley and Pakes, that a plant decides to continue production if the expected value of doing so is greater than the value of exiting, where this expectation is based on what the plant knows at time $t-1$ – i.e., the identification of this survival probability does not depend on a particular functional form, or a standard exclusion restriction.[25]

We consider the following productivity process:

$$\begin{aligned}
\omega_{it} &= g_\psi(\omega_{it-1}, \underline{\omega}_{it}) + \xi_{it} \\
&= g_\psi(\omega_{it-1}, \rho_{t-1}^{-1}(\omega_{it-1}, \mathcal{P}_{it})) + \xi_{it} \\
&= g_\psi(\omega_{it-1}, \mathcal{P}_{it}) + \xi_{it}.
\end{aligned} \tag{8}$$

Note that this process can vary between minimills and vertically integrated plants; as we have seen in the OLS regressions, vertically integrated plants slowly catch up to minimills.

We recover estimates of the production function coefficients, $\boldsymbol{\beta}$, by forming moments on this productivity shock ξ_{it}, and we rely on the following moments:

[25]Formally, there are two different nonparametric functions controlling for productivity and the lower bound threshold for productivity, and it is precisely the notion that information available to the plant at $t-1$ is used to form predictions of future profits, whereas current state variables provide information about current unobserved productivity shocks. See Olley and Pakes (1996) for more details.

$$E\left(\xi_{it}(\boldsymbol{\beta})\begin{bmatrix} l_{it-1} \\ m_{it-1} \\ k_{it} \end{bmatrix}\right) = 0. \tag{9}$$

The identification of these coefficients relies on the rate at which inputs adjust to these shocks. In particular, we allow capital have a one-period time-to-build, so that capital does not react to current shocks to productivity (ξ_{it}). Plants do, however, adjust their labor and intermediate input use (scrap, energy, other material inputs) to the arrival of a productivity shock ξ_{it}.[26]

4.1.3 Production function coefficients and technology premium

We consider different specifications for the production function in Tables 3 and 4, which present estimates of the production function for both GMM estimates – i.e., those that use the Olley-Pakes approach outlined in the previous section, versus estimates using OLS. While Table 3 is concerned with differences in the production function between minimills and vertically integrated plants, Table 4 focuses on the effects of including plant-level price deflators for both inputs and output while pooling across both technologies.

Technology-specific production functions

We start by estimating production function coefficients that are either allowed or not to differ by technology, and use either GMM or OLS. Columns I and III in Table 3 show pooled estimates, while Columns II and IV have interactions between inputs and an indicator for whether a plant is vertically integrated.

The production function coefficients, across all specifications, are stable and imply reasonable estimates of returns to scale and output elasticities. An important test for our purpose is to check whether minimills and vertically integrated producers rely on different production functions. Note that none of the interactions between inputs and an indicator for whether a plant is vertically integrated are statistically significant – i.e., we cannot reject the hypothesis that the production function coefficients are identical for both technologies. Moreover, we also run an F-test on the joint significance of the interacted coefficients in Column II (OLS). In doing so, we cannot reject – at the 11-percent level – that both technologies produce under the same output elasticities of labor, materials, and capital.[27]

[26] See De Loecker (2011) for a detailed discussion of the inclusion of additional exogenous state variables in the investment control. All our results are invariant to modifications of the timing assumptions discussed in the main text. Our approach is flexible and can allow for a variety of production functions combined with various assumptions on the variability of inputs, as well as the use of alternative proxies such as intermediate inputs – i.e. a modified Levinsohn and Petrin (2003) estimator. In particular, we consider the case in which labor is a state variable, and our results are robust to this alternative. See Online Appendix D.1 for more discussion on some of the technical issues.

[27] One might also ask if the subsequent analysis in this paper is also affected by the focus on a single production function for both technologies. In Section 6.1, we show that the point estimates for our productivity decompositions are virtually identical if we allow (or do not allow) for different production functions by technology. However, we lose a large amount of statistical power by allowing for this additional flexibility.

At first, it might seem surprising that, say, the coefficient on materials does not vary across technologies. However, note that this coefficient reflects the importance of the total use of intermediate inputs in final production. Aggregating over the various intermediate inputs into M_{it} masks the distinct inputs used in production, which differ tremendously by technology.[28] Section D.3 of the Online Appendix presents a models that allows for different bundles of total intermediate inputs M across technologies, but these bundles themselves are produced using a Leontief fixed-proportion technology, where the weights across the various inputs are technology-specific. This structure has the appeal that different intermediate inputs, such as coal and iron ore, are non-substitutable for each other, but the entire bundle of intermediate inputs M has the standard Cobb-Douglas elasticity of substitution with respect to labor and capital.[29]

Price Deflators and Productivity Estimates

Table 4 present estimates of the production function for different price deflators, pooling across all plants in the industry. Columns I and II show estimates where we deflate both inputs and outputs using plant-specific price deflators, while Columns III and IV show the case where we use an industry-level output price deflator, and Columns V and VI show estimates with an industry-level input price deflator. Each pair of columns corresponds to the case where we first use GMM and then shows OLS results to highlight the importance of our corrections. Finally, we compute productivity using the estimates of the production function coefficients, and we project productivity against an indicator of whether a plant is a vertically integrated producer, along with year fixed effects. We call this coefficient the VI premium.

Four main results emerge from this analysis. First, minimills are, on average, more productive, as indicated by a negative coefficient on the VI dummy. Under specification II (OLS), minimills have a two-percent-higher TFP than vertically integrated producers, but this is not statistically significantly different from zero. This result is surprising, both since we have shown that minimills have higher measures of profitability, and since these plants show large increases in market share over the sample period.

Second, the differences in the estimates of the VI premium demonstrate the importance of controlling for plant-level price differences. When we correct for plant-specific output prices, we find that the minimill TFP premium moves from 3.8 to 7.5 percent and becomes statistically significant. The impact of including detailed price data on the technology coefficient is expected since we know from Figure 3 that VI plants are active in the relatively higher-quality segments, where output prices are higher. Therefore, when we do not properly deflate the sales data, the productivity premium for minimills is dampened. However, omitting the correction for input prices in Column IV does not substantially affect the VI premium, moving it from 7.5 percent in Column I, to 7.6 percent in Column IV. Note, also, that

[28] For instance, in 2002, Iron and Steel Scrap represented 42 percent of the coded material inputs for minimills, and Coal for the production of Coke represented 15 percent of the coded material inputs for vertically integrated plants. Table C.2 in the Online Appendix shows the breakdown of materials for both minimills and vertically integrated plants.

[29] For example, a minimill could directly buy direct-reduced iron (DRI) instead of producing this in-house, thereby freeing up labor and capital for production.

the estimates of the output elasticities are virtually identical whether or not we use plant specific-prices to deflate inputs and output.

To understand the impact of our price corrections, we find it helpful to write out the potential bias induced by not properly deflating either output or inputs. Without deflating, the following equation is estimated on the data:

$$r_{it} = \beta_l l_{it} + \beta_k k_{it} + \beta_m m_{it}^E + \omega_{it} + p_{it} - \beta_m p_{it}^M + \epsilon_{it}. \tag{10}$$

This equation relates plant-level revenue (r_{it}) to (physical) labor, capital, and intermediate input use that potentially still contains input price variation (m_{it}^E). In addition to unobserved productivity, and a standard error term (ϵ), the production function includes two price errors: the output and the input price. Two observations are important to make. First, we could obtain biased production function coefficients, since input use is frequently correlated with output and input prices. Second, our estimate for productivity will be contaminated by output and input price variation, and we would not correctly identify the productivity difference between minimills and integrated plants. We refer the reader to De Loecker (2011) and De Loecker et al. (2012) for more details on the impact of unobserved output and input prices, respectively.

Third, the selection and simultaneity biases understate the productivity advantages of minimills. Attenuation bias lowers the estimated returns to scale. Since VI plants are larger than minimills, this will make VI plants look more productive than they really are. Likewise, simultaneity typically results in a downward bias on the capital coefficient. Indeed, the estimated capital coefficient is 0.050 in Column II (OLS), while it increases by 60 percent, to 0.079, in Column I (GMM) once we correct for simultaneity and selection. Since VI plants are more capital-intensive than minimills, this will again make VI plants appear more productive.[30] In all the subsequent analysis, we rely on estimates of productivity, ω_{it}, from Column I of Table 4. We also show all our main results using various specifications discussed in Table 4 to give an idea of how differences in specifications of the production function spill over into the subsequent analysis.

Technology does not explain *all* the differences in productivity, as the standard deviation of ω_{it} is about 30 percent, while differences in technology account for an eight percent gap in productivity. Thus, there remain substantial productivity differences between producers, both within and across technology types. This finding sits well with recent evidence on the dispersion of productivity across producers in narrowly defined industries. See Syverson (2011) for a recent survey.

We have exclusively compared plants of different technology along one dimension: total factor productivity. While there are good reasons to focus on this variable, it is equally interesting and im-

[30] A capital coefficient of 0.079 is not exceptional for a gross-output production function. For some validation of this coefficient, it is useful to remark that the sum of the material and labor share is 0.88. Under the assumptions that underlie the first-order approach to the estimation of production functions, this would imply a capital coefficient of 0.12 under constant returns to scale, and a smaller coefficient on capital if there is any market power. Note, as well, that increasing the capital coefficient would lead to finding an even larger for role for reallocation towards minimills since vertically integrated mills are more capital-intensive, so increasing the capital coefficient makes these appear less productive.

portant to consider different measures of firm performance. While in most applications, estimates of productivity (ω_{it}) and direct measures of profitability will be very similar due to the fact that output and input prices are included in the productivity residual, they can be quite different in our setting.[31]

As already discussed in section 3.2, minimills are also superior in other measures of performance such as profit margins and the rate of return on capital.[32]

4.2 Alternative productivity drivers

In this section, we explore various potential alternative drivers of productivity growth in the steel industry. The goal of this section is not to rule out these alternate mechanisms. We simply wish to show that our technology mechanism is unaffected by controlling for the following alternatives: Firm-level characteristics, geography, and international trade do not appear to play a role in explaining the differences in productivity between minimills and vertically integrated producers.

4.2.1 Management practices and ownership

Our analysis, thus far, has been focused on plants. To the extent that better plants are managed by better firms, we have, so far, attributed productivity differences across plants to technology, rather than to better management – that is that more-productive plants, regardless which technology they use, are better-managed, or belong to more efficiently organized firms. The potential role for firm-level variables to explain productivity differences is plausible, given the recent findings of Bloom and Van Reenen (2010). They present empirical evidence that measures of productivity, like the one we use, are correlated with various management practices, reflecting human resource (HR) practices and organizational design. Likewise, Ichniowski et al. (1997), using detailed data on rolling lines at U.S. steel mills, find that better HR practices lead to higher productivity. Their results confirm recent theoretical models that stress the importance of complementarities among work practices.

To check whether the minimill premium in our sample period is driven by better-managed firms, or by *any* particular kind of firm-specific ownership structure, we compare minimills to VI plants *within* the same firm, and time period, by regressing productivity on technology, and a firm-year fixed effect. Table 5 presents the results. We start out in Column I with a base premium of 7.4 percent without firm fixed-effects. We find an almost identical productivity premium for minimills, of 8.4 percent, when including a firm-year fixed effect (Column II). These results suggest that the minimill productivity premium was not driven by a particular allocation of minimill plants to more-productive firms with, say, better management or human resource (HR) practices.[33]

[31] See De Loecker and Goldberg (2014) on how exactly they relate to each other.

[32] In addition, we also checked whether exit relates to the plant's profitability. To do this, we ran regressions of exit in a five-year window – i.e., plant exit in 1992 given that the plant was active in 1987, on profitability, capital, an indicator on whether a plant is vertically integrated, and year controls. The marginal effects of this regression are presented in Table B.5. We find that more profitable-plants, measured either by rate of return or profit margin, are less likely to exit.

[33] Our results do not contradict those presented by Ichniowski et al. (1997), who rely on a sample of 17 rolling mills collocated with vertically integrated plants in the United States and, therefore, omit minimills from the analysis. Thus, there

Finally, including firm fixed effects does not rule out an effect of management. If management practices differ between plants at the same firm, and these intra-firm differences in management are precisely aligned with the technology used in production, then we could still attribute management effects to minimills. However, while we think that this story is improbable, it would take historical plant-level data on management to rule it out, and, the Census data during our sample period do not track this type of information.[34]

4.2.2 Geography

Although steel production has historically been concentrated in a few regions in the U.S., there is still considerable variation in activity across regions. In 2002, 63 percent of steel was produced in the Midwest – i.e., Illinois, Indiana, Michigan, Ohio, and Pennsylvania – while this figure was 75 percent in 1963. We check whether regional patterns influence our results by incorporating a full set of state-year dummies, in a regression of productivity on our measure of technology. Column III, in Table 5 shows that the substantial minimill premium is largely unaffected when including state-time fixed effects. This result reflects that minimills are, on average, 10.2 percent more productive than integrated producers in the same state and year (Column III). Furthermore, this result is robust with respect to including technology-year interactions.

Finally, in Column IV, we include a joint firm-state-year fixed effect and find that the technology premium is still strongly positive and significant, but with a point estimate of 18 percent.[35] This suggests that minimills are vastly more productive, even when we compare a minimill and a vertically integrated plant owned by the same firm, and located in the same state. The results in Table 5 indicate that the productivity premium for minimills is robust, and is not an artifact of a particular selection mechanism that operates at the firm or regional level.

4.2.3 International Trade

Over the last four decades, the U.S. steel sector has faced stronger competition from foreign producers. For our purposes, the relevant question is whether the mere increase in import competition could explain the rapid productivity growth in the industry.

is no information on the relative performance of minimills. Moreover, the size of the productivity effects (in gross-output terms) found in Ichniowski et al. (1997) are equivalent to between 2.7 and 3.5 percent. See Table B.6 for more details on these calculations.

[34]The new wave of economic Census will contain a Management and Organization Practices Survey (MOPS). See World Management Survey and `http://bhs.econ/census.gov/bhs/mops/` for more on this recent addition. Unfortunately, in our sample, 1963-2002, the MOPS survey did not exist. Therefore, we cannot empirically test the role of management directly in the data that are readily available. MOPS is now part of the 2010 ASM, which would allow for only a cross-sectional comparison of, say, minimills to integrated plants. Whether or not there were any differences in management practices across technologies in 2002, it would not help separate out the impact of the entry of minimills on industry aggregate productivity growth, over the period 1963-2002.

[35]About nine percent of firms own both minimills and vertically integrated plants, and these firms produce 43 percent of output in the industry.

Table 6 lists the change in imports and import penetration rate across the U.S. manufacturing industries (4-digit SIC codes) and compares these with those for the steel industry. The upper panel lists the total imports and shows that the steel sector's imports increased by four percent, versus 66 percent for the average manufacturing industry. The bottom panel reports the import penetration ratio and highlights that international competition increased across all U.S. manufacturing industries; steel was no exception. Yet there was a slower increase in international competition for the steel industry relative to most sectors in manufacturing, with the import penetration ratio increasing by eight percent in steel versus 15 percent for the rest of manufacturing. However, productivity growth in the steel industry, as shown in Table 1, was well above the average for manufacturing. Thus, it is not the case that the exceptional productivity growth in steel was contemporaneous with an exceptional increase in import competition for steel producers.

We examine the statistical relationship between productivity growth and the change in the import penetration ratio over the period 1972-1996. Specifically, we run the following regression: $\Delta\Omega_I = \gamma_0 + \gamma_1 \Delta\text{import penetration}_I + \nu_I$ across the entire sample of four-digit SIC87 industries I, where Δ is the difference over the 1972-1996 period, and we weigh observations by the industry's share in total manufacturing production. Table B.7 in the Online Appendix presents the results of these regressions in detail. This regression predicts only an eight-percent increase in productivity in the steel industry, given the steel industry's increase in import penetration.[36] Put differently: The change in international competition can explain, at most, one third of the productivity growth.[37]

One might worry that the effects of international competition were more pronounced for vertically integrated producers than for minimills, thus affecting the interpretation of our results. Therefore, we look at whether import shares differed across products. As discussed previously, minimills were primarily active in the bar segment, while vertically integrated producers produced both bar and sheet products. When we break down imports and exports by product, we find that imports show a rise for bar products produced by minimills that is similar to that of sheet products, which minimills do not produce.

In addition, since vertically integrated producers were historically more concentrated in the midwest, while minimills were more evenly distributed across the country, including in coastal areas, we might worry that vertically integrated plants were more insulated from foreign competition. However, in the previous subsection, we showed that the productivity advantage of minimills is robust to controlling for regional differences in the form of state fixed-effects.

[36] We construct a matched production-trade database at the four-digit SIC87 level using the NBER Manufacturing Database and the U.S. Trade Database.

[37] These types of estimates are further subject to various biases and measurement problems. Identifying the impact of foreign competition on industry performance is further complicated by endogenous changes in international competition, as well as by reversed causality from productivity growth to international trade.

4.2.4 Unions

One might also be concerned that differences in the performance of minimills and vertically integrated producers were due not to technology, but to higher unionization rates at vertically integrated producers. We address this issue in several ways.

First, much of the variation in unionization between minimills and vertically integrated plants stems from geographic differences in state laws on unionization. In particular, many states in the south of the United States have "right to work" laws that make it difficult for workers at a plant to form a union. However, our previous work in Subsection 4.2.2 found that controlling for geography had no bearing on the measured productivity advantages of minimills.[38]

Delving deeper into controls for unionization, in our reading of discussions of unionization, a firm's workers are usually either unionized or not unionized across all of its plants within the state. Column IV of Table 5 runs regressions of plant-level productivity on the technology dummy and firm-state-year fixed-effects.[39] Thus, we control for any productivity difference that might exist between states and time and within the firm. We find that the productivity premium for minimills is somewhat higher, at 18 percent, when we look for productivity differences within the firm and state.

Second, we go beyond the simple notion of such a control, and we rely on data on union membership rates from 1983 to 2002, with the information broken down either by state, or by industry. Table B.8 in the Online Appendix lists the rates for the steel industry and compares it to the average for all of manufacturing. We find that steel unionization intensity – as measured by the membership rate – fell by exactly the same rate as the average in all of manufacturing. Therefore, we invoke the same logic as in the (aggregate) import case: The unionization rate cannot explain the differential productivity growth for steel compared to the average for the manufacturing sector as a whole.[40]

Third, we find it useful to revisit the existing literature on unions and productivity. Schmitz (2005) finds evidence that unions have a strongly detrimental impact on productivity in the iron-ore industry. However, other studies, such as Clark (1980)'s study of the cement industry, find productivity *improvements* due to unions. To parse throughout the industry-level evidence on the impact of unions, a nice collection of studies is Medoff and Freeman (1984), who find few positive or negative effects of unions on productivity. Our findings are, therefore, not inconsistent with the broader literature.[41]

[38] Another way to refine this is to focus on those states in which unionization rates are very low. However, state and year controls are the most important factor in explaining the unionization rate in a state-year panel data. The R^2 of the union membership rate on state and year dummies (separately of course) is 87%.

[39] The only direct evidence we found is by Arthur (1999), who mentions that about 50 percent of minimill workers are unionized. So even among minimills, half of the workers are unionized, which further strengthens our hypothesis that variation in unionization is not a clear driver for the productivity premium.

[40] A summary of our argument is in Figure B.1 in the Online Appendix, where we plot the initial union membership rate (for 1983) against that of 2002. The size of the circle is the employment weight of a sector in total manufacturing employment. We insert both the 45 degree line and the line of best fit. The steel industry is indicated in the full grey circle, and it lies exactly on the line-of-best fit. This, together with the fact that steel's aggregate productivity growth is an order of magnitude bigger than the median manufacturing sector, leaves little scope for the union story.

[41] The main obstacles for doing an analysis of the role of unions with micro data in the steel industry, or any industry for this matter, are summarized by Lee and Mas (2012).

4.2.5 Distinguishing between competing forces

We have put forward evidence of a robust productivity premium for the new technology (minimills). However, this does not rule that other factors, such as those discussed above, can simultaneously operate and lead to additional productivity gains. More specifically, in the case of imports and unions, we showed that, quantitatively, the steel industry's experience in import and unionization rates is not dissimilar from the average for U.S. manufacturing, while its TFP growth is exceptional. However, this does not imply that the increase of imports, and its associated import threat, and decreased unionization, had no role in shaping overall manufacturing productivity. Previewing our decomposition, we think that it is useful to distinguish the impact of these *industry-wide* effects from the differences in productivity across technology. In this paper, though we focus on the latter, we do not rule out the possibility of additional drivers of productivity growth.

Our ultimate aim is to explain the change in aggregate productivity. The distinction between plant-level regressions and aggregate productivity is particularly important in how we think these *other factors* could potentially plague our analysis. The next section deals precisely with the issue of separating the various channels – i.e., distinguishing between *within-plant improvement* and *reallocation across plants*. Our results so far indicate that, at a minimum, there is a potential for the arrival of minimills to impact aggregate productivity due to their superior efficiency.

5 The Role of Reallocation

We rely on our productivity estimates to verify the importance of reallocation, both across and within technologies, in productivity growth. We consider both static and dynamic decompositions, which enables us to investigate the importance of entry and exit in productivity growth. We relate a direct measure of competition – markups – to the reallocation analysis by connecting markups to the analysis of reallocation, which relates market shares to productivity. Finally, we provide some indications of the likely welfare effects of the arrival of minimills.

Following Olley and Pakes (1996), we consider industry-wide aggregate productivity (Ω), the market share (denoted by s_{it}) weighted average of productivity ω_{it}. In particular, we rely on the following definition of aggregate productivity: $\Omega_t \equiv \sum_i s_{it}\omega_{it}$, which is different from the unweighted average of productivity $\overline{\omega}_{it} \equiv \frac{1}{N_t}\sum_i \omega_{it}$.

5.1 Static Analysis: introducing a between-technology covariance

In recent work, Bartelsman et al. (2009) discuss the usefulness of the Olley and Pakes decomposition methodology. They highlight that the positive covariance between firm size and productivity is a robust prediction of recent models of producer-level heterogeneity (in productivity), such as Melitz (2003). We follow the standard decomposition of this aggregate productivity term (also referred to as the OP decomposition) into unweighted average productivity and the covariance between productivity and market share.

Definition Olley-Pakes Decomposition

$$\Omega_t = \overline{\omega}_t + \sum_i (\omega_{it} - \overline{\omega}_t)(s_{it} - \overline{s}_t) = \overline{\omega}_t + \Gamma_t^{OP}, \tag{11}$$

where Γ_t^{OP} is the Olley-Pakes Covariance.

The same decomposition can be applied by technology type ψ – i.e., treating MM and VI producers as if they belong to separate industries – and this decomposition will help us understand whether the average productivity of the different technology types evolved differently, and whether there is any substantial reallocation across producers of the same vintage. We call this the *within* decomposition. The market share of each technology is denoted $s(\psi)_t = \sum_{i \in \psi} s_{it}$. Likewise, the type-specific aggregate productivity is $\Omega_t(\psi)$, while the average productivity within a technology type is $\bar{\omega}_t(\psi)$.

Definition Within-Technology Decomposition

$$\begin{aligned} \Omega_t &= \sum_{\psi \in MM,VI} s_t(\psi) \left(\overline{\omega}_t(\psi) + \sum_{i \in \psi} (\omega_{it} - \overline{\omega}_t(\psi))(s_{it}(\psi) - \overline{s}_t(\psi)) \right) \\ &= \sum_{\psi \in MM,VI} s_t(\psi) \left(\overline{\omega}_t(\psi) + \Gamma_t^{OP}(\psi) \right). \end{aligned} \tag{12}$$

This within decomposition reflects both the change in the actual type-specific component, the unweighted average and the covariance term, as well as the type-specific market share.

To measure the importance of reallocation of resources *between* technologies, we interact the productivity index with the type-specific market share, $s_t(\psi)$. We apply the same type of decomposition, but now the unit of observation is a type; hence, one can think of two plants, an aggregate minimill and an aggregate vertically integrated producer. This allows us to isolate the between-type reallocation component in aggregate productivity. Denote as $\overline{\Omega}_t = \frac{1}{2} \sum_\psi \Omega(\psi)_t$ the industry productivity if minimills and vertically integrated producers have the same market share – i.e., akin to the unweighted average of both technologies, we obtain:

Definition Between Technology Decomposition

$$\Omega_t = \overline{\Omega}_t + \sum_{\psi \in MM,VI} (s_t(\psi) - 1/2)(\Omega_t(\psi) - \overline{\Omega}_t) = \overline{\Omega}_t + \Gamma_t^B, \tag{13}$$

where Γ_t^B is the "Between Covariance" measuring the extent to which the resource reallocation towards minimills contributed to the aggregate productivity for the entire industry. Note that since the average market share is always one half, when the market share of minimills equals the market share of vertically integrated producers, the between covariance term Γ_t^B is zero, regardless of the productivity difference between the two types.[42]

Finally, we can group the within-technology and the between-technology decomposition together to explain aggregate TFP:

$$\Omega_t = \frac{1}{2} \sum_{\psi \in MM,VI} [\bar{\omega}_t(\psi) + \Gamma_t^{OP}(\psi)] + \Gamma_t^B. \tag{14}$$

Note that equation (14) allows us to explain changes in productivity, through i) changes in the average productivity of minimills and vertically integrated plants ($\bar{\omega}_t(\psi)$); ii) changes in the covariance between output and productivity for both MM and VI plants ($\Gamma_t^{OP}(\psi)$); or iii) reallocation across technologies (Γ_t^B).

5.2 Static reallocation analysis: results

Table 7 shows the various cross-sectional decompositions of aggregate productivity – Olley-Pakes, Between, and Within – looking at their change from 1963 to 2002.

Three important results emerge. First, the Olley-Pakes decomposition of aggregate productivity across all plants shows that the average producer became 15.7-percent more productive between 1963 and 2002. In addition, the reallocation towards more-productive plants was an important process in increasing productivity, generating a 6.4-percent increase from 1963 to 2002. Thus, aggregate productivity went up by 22 percent, of which one third was due to the reallocation towards more-productive plants. This indicates that reshuffling of market shares across producers was an important mechanism through which the industry realized productivity gains.

Second, we find a large role for the between-technology reallocation component (Γ^B). In 1963, the between covariance was -6.6 percent, as the older vintage of VI plants had both lower productivity and greater market share. The between covariance Γ^B then became less negative as the minimills, which have a productivity premium, gradually increased their market share. Towards the end of the sample period, minimills had about half of the market, which mechanically implies a zero between reallocation component. This between reallocation of output from VI plants to MMs accounts for a 5.1-percent increase in productivity, 23 percent of the overall productivity growth of the industry. The fact that the arrival of a new production technology can account for changes in the covariance term is critical since this suggests an important role for technology in explaining the reallocation that led to a sharp increase in productivity.

Third, drilling down to the technology type, we see that minimills increased their aggregate TFP ($\Omega(MM)$) by ten percent, while vertically integrated plants raised their aggregate TFP ($\Omega(VI)$) by 24 percent. Interestingly, the reason that vertically integrated producers caught up with minimills is

[42] Given the substantial entry of minimills that typically entered on a smaller scale and remained smaller, we can expect the covariance term to be negative –i.e., the more-productive plants have a smaller market share. But we do expect this covariance term to become less negative over time, as Figure 2 shows that minimills started with a very small market share and gradually captured a larger part of the market.

not changes in the Olley-Pakes covariance term $\Gamma_t^{OP}(\psi)$, whose contribution to productivity growth was 3.7 percent for minimills and 4.4 percent for vertically integrated producers. Rather, it was the much higher increase in average plant productivity for vertically integrated producers ($\overline{\omega}_{it}(VI)$) of 18.4 percent, versus a $\overline{\omega}_{it}(MM)$ of 5.4 percent for minimills.

So far, our analysis points to a large impact of minimill entry on shaping overall industry productivity. We find that about 44 percent of total aggregate productivity growth can be directly attributed to minimills, with 23 percent due to reallocation away from the old technology and the remaining 21 percent due to productivity improvements at minimill plants, which captures productivity improvements across all minimills, such as learning by doing and technological change.[43]

5.3 Dynamics: the role of entry and exit

The above decomposition masks the potential impact of entry and exit on aggregate productivity. The average productivity term $\overline{\omega}$ mixes changes in productivity inside plants, with changes in the distribution of productivity due to entry and exit. A similar concern also affects the measured covariance terms. We turn to this and consider a dynamic version of our decomposition. Let us consider three distinct sets of producers for a given time window $t-1, t$, where t is a ten-year window: incumbents ($\mathcal{A}$), entrants ($\mathcal{B}$) and exiting plants ($\mathcal{C}$).[44] Using these sets, we can write aggregate productivity growth, $\Delta\Omega_t$, as:

$$\underbrace{\sum_{i\in\mathcal{A}} s_{it-1}\Delta\omega_{it}}_{\text{Plant Improvement}} + \underbrace{\sum_{i\in\mathcal{A}} \Delta s_{it}\omega_{it-1} + \sum_{i\in\mathcal{A}} \Delta s_{it}\Delta\omega_{it}}_{\text{Reallocation}} + \underbrace{\sum_{i\in\mathcal{B}} s_{it}\omega_{it}}_{\text{Entry}} - \underbrace{\sum_{i\in\mathcal{C}} s_{it-1}\omega_{it-1}}_{\text{Exit}} . \tag{15}$$

The first term is denoted *Plant Improvement*; the next two on are the *Reallocation* term, and the last two terms are the *Entry* and *Exit* components. The above decomposition directly isolates the net-entry effect on aggregate productivity by verifying the importance of the last two components in total productivity growth. Finally, to isolate the role of entry and exit for each types of technology, we expand the above by computing equation (15) by technology type ψ. When we refer to the total impact of reallocation, we group all terms except for the plant-improvement component.

Table 8 presents the decomposition across all plants and by technology.[45] The first row restates the 22-percent productivity growth in the U.S. steel sector, but finds far faster growth for vertically integrated plants than for minimills.

Across the entire sample period, over which productivity increased by 22 percent, the *plant improvement* component accounted for a 9.5-percent increase in aggregate productivity (or a 43-percent

[43] We do not pursue an explicit analysis of the learning-by-doing effects at minimills, since our data do not contain the level of detail needed for us to credibly infer this process. See Benkard (2000) for such an analysis, and what type of data are key to identifying learning by doing. Our data do suggest that there is no substantial vintage-effect for minimills. The dynamic decompositions will shed more light on this dimension.

[44] This decomposition has been suggested by Davis et al. (1996) and has been used in other empirical work, such as De Loecker and Konings (2006).

[45] We also analyzed the changes over a ten-year period. Due to Census disclosure rules, we cannot present for shorter time windows, and the results are very similar.

share), while reallocation and net entry are responsible for the remainder. Thus, the total share of reallocation in aggregate productivity growth, including both the reallocation induced by market-share reallocation across incumbents and the net-entry process, is two-thirds.

A clear picture emerges when we move to the decomposition by technology. The main driver of productivity growth for minimills is the plant improvement component of 11.8 percent, capturing the technological change in minimills. This is suggestive of the substantial learning by doing that took place in minimill production– in particular, learning how to produce higher-quality steel – over the sample period. The reallocation component is negligible.

The same analysis of VI producers yields substantially different results: The plant improvement component, of 9.3 percent, is smaller than that of minimills (11.8 percent), and the net entry term of 3.8 percent is almost 17 percent of total industry productivity growth over the sample. Most noteworthy is that the reallocation term of 11.3 percent is responsible for 23 percent of industry-wide productivity growth.

In the last row of Table 8, we restate the distinct role of the net-entry process across technologies. We present the productivity premium of entrants, compared to the set of exiting plants. Across the entire sample period, VI entrants were 4.4-percent more productive than those VI plants that exited the industry. New minimills, on the other hand, entered with no specific productivity advantage.

To summarize, we find a drastic difference in the role of reallocation between technologies. The productivity growth of minimills was entirely due to common within-plant productivity growth, whereas integrated producers' productivity growth came from the reallocation of resources *across* producers. In the next section, we focus on the role of reallocation among vertically integrated producers, which was a key driver of productivity growth among producers relying on the old technology, and consequently, triggered productivity growth for the industry as a whole.

5.4 Catching up of the old technology

So far, we have shown that a substantial part of the industry's productivity growth can be accounted for by the arrival of the new technology and its own technological progress, capturing about half of the productivity growth in the industry. The entry of the new technology, however, spurred a dramatic reallocation process in the incumbent technology, leading to a sharp increase in productivity– where the exit margin played a key role. It is, therefore, natural to ask how incumbents became more productive. From our various decompositions, we already know that the exit of inefficient producers was a key driver, in addition to the reallocation among existing producers.

To uncover the underlying mechanism, we incorporate the product space of the industry. We know from Figure 3 that the market-share trajectories of minimills for, broadly speaking, two product categories – *bar products* and *sheet products* – were very different. Indeed, minimills took over bar products, but not sheet products. Therefore, we verify whether the substantial productivity gains among (surviving) VI producers over our sample period were related to the product-market competition – i.e., did VI producers of bar products exit, leaving only those VI producers specializing in sheet products?

In other words: How important was increased competition, due to minimill entry, for incumbents's productive efficiency?

The distinction between the two product groups is relevant to the extent that (1) there exists a productivity difference between bar producers and sheet producers, and (2) survival is related to specialization. A potential third component would be the change in product specialization at the plant level over time. However, we find very little change in product specialization over time, which we discuss in more detail in Online Appendix F; thus, this mechanism cannot generate within-plant productivity improvements.

In order to verify whether this mechanism is important in the data, we first test whether plants specializing in *sheet products* were, on average, more productive, than those specializing in *bar products*. Subsequently, we ask whether the product specialization variable predicts plant survival. We run both tests on the total sample of plants in our data, and on the subsample of VI producers. In the latter, we compare plants of the same technology and verify whether product specialization can explain the rapid productivity growth among the group of VI producers.

Table 9 estimates both a technology and sheet-specialization productivity premium for a number of specifications, where sheet specialization refers to the share of a plant's revenue accounted for by sheet products.[46] In Panel A, we consider all plants in the industry, and while controlling for technology and an exhaustive set of fixed effects, find a robust and significant productivity advantage for plants specializing in *sheet products*. Even if we compare plants of the same technology, within the same firm and in the same year in Column IV, we find a 12-percent productivity premium for plants that completely specialized in sheet. In Panel B, we focus on the VI producers, and find a similar premium. These results, therefore, suggest that the rapid productivity growth of VI producers was due to the reallocation from bar to sheet producers. The latter is consistent with the market-share trajectories presented in Figure 3, which showed MM taking over bar products but not sheet products.

Taking the sheet productivity premium as given, we verify whether VI producers producing primarily sheet products had a higher likelihood of survival. In Table 10, we present survival regressions, where we run an indicator of plant survival – whether a plant that was in active in 1963, survived until 2002 – against plant technology and sheet specialization.[47] In Panel A, we consider all plants in the industry and find that the sheet specialization ratio variable has a strong positive impact on a plant's survival probability, holding fixed its technology. Indeed, a plant that was fully specialized in sheet had a 31-percent-higher probability of surviving than a plant that was fully specialized in bar. This is a very large effect, as plants have a 33-percent likelihood of survival to begin with. Moreover, this effect is robust to controlling for the plant's capital and productivity– standard predictors of plant survival.[48]

[46] For all practical purposes, minimills do not produce sheet products. Moreover, there is little year-to-year variation in the share of revenues accounted for by sheet products within a plant as discussed in Online Appendix F. This suggests that it is difficult to alter the product mix at the plant level. Given the lack of within-plant variation in sheet specialization, regressions with plant-level fixed effects will have little power to identify the productivity premium of sheet producers.

[47] These results are robust to looking at survival from 1967, 1972 or even 1977, until 2002. Likewise, these results are also robust to looking at survival until 1997 and 1992.

[48] See Collard-Wexler (2009) and the references therein.

The productivity difference between sheet and bar producers is relevant only to the extent that it exists among integrated producers. In Panel B, we focus on VI producers and find a very similar effect: VI producers specializing in sheet products in 1963 had a 31-percent-higher probability of surviving to the year 2002. We note that predicting plant survival over a 40-year period is a very demanding task. Even when our sample size is reduced to 78 VI producers active in 1963, we obtain a t-statistic of 1.6 on the sheet-specialization variable, while controlling for capital and productivity.

Thus, the joint productivity and survival premium for sheet producers help explain the overall productivity growth of VI producers in the aftermath of minimill entry. Minimills increased competition in the bar market, leading to the exit of inefficient VI producers. As a consequence, the set of remaining VI producers was more productive due to an increased concentration in the *sheet product* market. This mechanism, therefore, manifests itself in substantially higher productivity of VI producers and a dramatic drop of VI's market share of bar products. In light of our decomposition results, presented in Tables 7 and 8, 30 percent of the industry's productivity growth was due to the reallocation process among VI producers, in which the specialization in *sheet products* seems to have played a crucial role. To obtain the 30-percent contribution, we sum the role of net-entry (0.07) and reallocation (0.23), in as listed in Table 8.

Finally, the only component we have not explained is the pure within-plant productivity growth component for VI producers, which, according to our results in Table 8, accounted for only 19 percent of aggregate TFP growth. This common shift of the production frontier for VI producers captures the direct technological innovations in steel making at integrated plants due to active investments, and improvements in technical efficiency. However, this leaves 81 percent of total productivity growth that can be attributed to the reallocation induced by minimill entry, as well as increasing productivity at minimills.

The fact that we cannot explain all productivity growth by the expansion of minimills is not surprising. We expect that 40-years of innovation in the engineering and management of vertically integrated plants led to increased productivity. Alternative drivers of productivity – such as management, imports and unions – are likely reasons for this within-plant improvement component. While it would be conceptually straightforward to regress $\bar{\omega}_t(\psi)$ against either measures of import penetration or unionization rates, this presents some practical challenges. In order to credibly identify the impact of such factors on (within-plant) productivity growth, we need to rely on exogenous variation across plants and time; therefore, this requires having either plant-level or industry-wide instruments.[49]

5.5 Market Power

The drop in demand for U.S. steel producers and the variation in the market-shares trajectories across products point to drastic changes in competition in the steel market. We argued that the entry of the minimill intensified competition for domestic steel producers, in particular for the bar segment of the

[49] For some recent work trying to tease out such an effect, see De Loecker (2011) and Bloom et al. (2011) on the impact of trade on productivity, where quota variation is used as a source of exogenous variation in international competition.

industry (see Section 3.2). In addition to this increased domestic competition, it is well known that international competition intensified through a substantial increase of imports. The increased competition is expected to have affected a plant's residual demand curve and, therefore, to impact its ability to charge a price above marginal cost. The change in the residual demand elasticity, and its associated markup response, are expected to have affected the reallocation across producers, as well.

We rely on the framework of De Loecker and Warzynski (2012) to: (1) show that markups indeed decreased as competition increased; and (2) show how lower markups are directly related to our measure of reallocation, the covariance of productivity and a plant's market share.

A nice feature of this approach is that we can generate measures of market power from our estimates of the production function. We rely on our production function framework to recover markups by technology type and plant. The core assumptions are that plants minimize costs, and at least one input is variable. Online Appendix D.2 presents the details of this approach.

The two ingredients for computing markups are the output elasticity of intermediate inputs, such as materials and energy, and the corresponding expenditure share of the input. The latter is directly observed in the data, whereas the output elasticities are recovered from our estimates of the production function β in section 4.1.3.

We compute markups (μ) by technology as obtained from technology-specific aggregate expenditures on materials ($E_t(\psi) \equiv \sum_{i\in\psi} p_{it}^M M_{it}$) and sales ($R_t(\psi)$), while relying on a time-invariant Cobb-Douglas output elasticity of the intermediate input (β_m):

$$\mu_t(\psi) = \beta_m \frac{R_t(\psi)}{E_t(\psi)}. \tag{16}$$

For our Cobb-Douglas production function, these markups are the proper technology-specific markups, where the markup by technology can be thought of as a weighted average markup across plants, and where the weights are given by the expenditure share on materials of a given plant in the total expenditures for plants using the same technology.[50]

5.5.1 Markup trajectory

Figure 4 plots the markup trajectory over 40 years for both MM and VI plants. Markups have steadily decreased over time and are consistent with the drop in prices and external measures of concentration reported for the steel sector. Markups were, on average, higher for minimills, confirming the results from the augmented production function estimation in Table 4. This is as expected since they produce more efficiently while competing in the same product market.

[50] To see this, use $c_{i\psi t} = \frac{E_{it}}{E_t(\psi)}$ in the share weighted markup expression for a type ψ, where $c_{i\psi t}$ is the share of an individual plant in the type's total: $\mu_t(\psi) = \sum_{i\in\psi} c_{i\psi t}\mu_{it} = \sum_{i\in\psi} c_{i\psi t}\beta_m \frac{R_{it}}{E_{it}} = \beta_m \frac{R_t(\psi)}{E_t(\psi)}$. The perhaps unattractive feature of a Cobb-Douglas production technology is that the output elasticities of intermediate inputs are time-invariant. Figure C.2 shows that the share of expenditures on intermediate inputs in total cost is rather constant across our sample period.

We can pursue the same strategy, and compare average markups across products. This is a particularly useful exercise since we have stressed the increased competition in the bar product market, at least up to the mid-1990s. Therefore, we expect that markups fall more in the bar market, as both the number of minimills and their share of bar output increased. However, in order to produce the trajectory of markups by product, we would need to estimate the markups for each plant and product. While this is conceptually straightforward in our framework, it requires recovering the allocation of input expenditures by product, for each plant. Unless we see fully specialized plants (into one product only), this is a challenging task.[51]

While we observe sales by product at the plant level, it is difficult to assign material expenditures to each of these products unless a plant is fully specialized into a single product. However, since minimills were almost completely specialized into producing bar products, at least up to the mid-1990s, we can interpret the markup trajectory of the minimills as representative of the trajectory of markups for bar products. We find that the average markup of minimills, standing in for bar producers, saw a sharp drop from 1.8 in 1963 to 1.1 in 2002. The markups for vertically integrated producers, who produce both bar and sheet products, fell only from 1.4 to about 1.2. We see this aggregate pattern as evidence that product market competition intensified due to the expansion of minimill production and led to lower margins, especially in the bar market.

5.5.2 Markups and reallocation

Markups fell at the same time that the covariance between output and productivity increased. Suppose that this fall in markups was due to firms' residual demand curve becoming more elastic. In other words, markups fell because the product market for steel became more competitive. This does not seem unlikely since there were far more steel producers in 2002 than in 1963 competing over a roughly similar market size.[52] A more elastic residual demand curve will accentuate the relationship between productivity and output. Furthermore, the increase in the residual demand curve for integrated firms is consistent with the increased competition from minimills, and a resulting decline in their market share. In the context of variable markups and trade liberalization, by Edmond et al. (2012) and Mayer et al. (2011) make a similar point. Thus, we expect the extent of competition to be linked to reallocation, which is the pattern we find in the data.

5.6 Welfare effects

While it is not the main focus of our paper, we can use our estimates of productivity growth, and our reallocation analysis, to make statements about the welfare effects of the entry of minimills.

We have good estimates of the production function and can, therefore, generate reliable estimates of the industry's supply curve. However, we do not have the same level of detailed data to engage in an

[51] See De Loecker et al. (2012)

[52] Total production in 1965 was about 130 million, and by 2000, it was about 112 million tons (American Iron and Steel Institute, 2010). Also see Figure 1, which presents the value of production and the number of plants.

econometric analysis of the industry's demand curve.

With this caveat in mind, we calculate the change in consumer surplus by presenting consumers in 1963 with 2002 prices. We previously found that, at a minimum, 51 percent of productivity growth could be attributed to the entry of minimills: 23 percent coming from the between reallocation (Table 7) and 28 percent coming from total minimill productivity growth (Table 8). Thus, we attribute 51 percent of the fall in prices for steel from 1963 to 2002 to minimills. We extrapolate counterfactual demand under these 2002 prices using various assumptions of the elasticity of demand. Table B.9 in the Online Appendix presents the consumer surplus gain in 1997 dollars, and the associated share of this change in consumer surplus over total sales of the industry. We also compute the total change in consumer surplus due to the fall in prices for steel from 1963 to 2002, irrespective of whether these are due to minimill entry or some other factors.

Depending on the exact elasticity of demand that we assume, we find that consumer surplus increased by between 17 and 23 billion dollars (in 1997 $) between 1963 and 2002. If we attribute 51 percent of this fall in prices to minimills, then minimills would be responsible for an increase in consumer surplus of between nine and 11 billion dollars. Put differently, our back-of-the-envelope calculations suggest that the reallocation towards minimills led to an increase in consumer surplus of between 13 and 16 percent of shipments in the steel industry.

Of course, this somewhat crude welfare analysis leaves out several important issues, one of which we already mentioned: We hold demand fixed, and impose a specific curvature of the demand curve. Another omission from this analysis is that over 400,000 workers left the industry, and we do not take into account the welfare implications of such a major transition.[53] A more complete welfare analysis should address these issues.

6 Robustness Analysis

We present the main results from our decomposition analysis using a variety of productivity estimates (as presented in Table 4). We discuss the robustness of our results and highlight the importance of our corrections in establishing a prominent role of technology in generating aggregate productivity growth. Finally, we consider an alternative measure of aggregate productivity, and its associated decomposition, which differs in the sense that reallocation can impact aggregate productivity only if the marginal product of inputs are not equalized across producers.

6.1 Robustness

Tables 11 and 12 present robustness checks on our decompositions of aggregate productivity growth. For several of the productivity estimates from using the specifications listed in Table 4, we produce

[53] Our data do not track employment out of the steel industry. Data from the LEHD program (Abowd et al., 2004) could presumably aid in identifying the reallocation of workers in the steel industry to other sectors.

the static and dynamic decompositions. The first column of Tables 11 and 12 rely on productivity estimates obtained using the production function coefficients of specification I in Table 4. We contrast these to results obtained using productivity estimates obtained without correcting for simultaneity and selection (Column II), and those obtained without correcting for unobserved output and input price differences across producers (Columns III and IV). We also include the results using technology-specific production functions (Column V), as discussed in Section 4.1.3 and presented in Column IV of Table 3.

The various components of the decompositions use plant-level estimates of productivity β, which rely on estimated production function coefficients and, thus, are also estimates. We use a block bootstrap routine to produce confidence intervals of the shares of each component. The 95-percent confidence intervals are given in Tables 11 and 12. Note that the main points on reallocation that we have discussed – such as the importance of the between covariance, the relatively faster growth of vertically integrated plants relative to minimills, and the more important role of reallocation and net entry for vertically integrated plants than for minimills – are statistically significantly at the 95-percent level for our baseline specification in Column I.

6.2 Importance of Corrections

Looking across the columns of Tables 11 and 12 shows that to obtain the correct quantitative effects of the entry of minimills on aggregate productivity, it is import to correct for unobserved productivity and prices when estimating the production function. What is particularly sensitive to the specification of the production function is the *between* decomposition. Indeed, the between component is 23 percent in Column I, which uses GMM, as opposed to ten percent in Column II, using OLS productivity estimates. These differences are statistically significant, as the 95-percent confidence intervals for the between technology share do not overlap. This is unsurprising, as Table 4 showed that the minimill productivity premium was far larger in Column I (GMM) than in Column II (OLS). These difference in the estimated productivity advantages of minimills spill over directly to the estimated magnitude of the between covariance. Likewise, if we had not controlled for plant-specific output prices, as shown by Column IV, we would have found a between technology share of 18 percent rather than 23 percent, even though this difference is not statistically significant. Again, the difference in the estimate between technology share reflects differences in the estimated minimill premium found in Table 4.

The role of entry and exit is altered by not correcting for plant-level prices and productivity errors in the production function. The impact of the exit process of vertically integrated producers is cut in half (from 16 to seven percent between Columns I and II), while the within-plant minimill improvements are underestimated (123 versus 87 percent from Column I to II). Correcting for simultaneity and selection is crucial to obtain reliable productivity measures and, more importantly, to measure the impact of entry and exit, an important part of our reallocation mechanism, on aggregate productivity.

Summing up, if we incorrectly ignored price variation across producers, the endogeneity of inputs, and the non-random exit of plants in the data, we would underestimate the reallocation mechanism by a factor of two. Our results suggest that the total effect of minimill entry on industry-wide productivity growth was 81 percent. This share drops somewhat when ignoring unobserved price and productivity heterogeneity. However, although we find a much larger magnitude, the role of technology is present even when using uncorrected productivity estimates, which adds to the robustness of the importance of our specific reallocation mechanism.

Allowing for technology-specific output elasticities, as shown in Column V, leads to virtually identical estimates of productivity growth and reallocation to those in Column I, which assume identical output elasticities across the two technologies. However, the 95-percent confidence interval around the various components is far larger in Column V than in Column I. This is to be expected given the insignificant interaction terms between inputs and the vertically integrated dummy in Table 3, as well as the associated loss in power when allowing for a more flexible production function.

6.3 Alternative decompositions

Recent work by Petrin and Levinsohn (2012) (PL hereafter) has highlighted that not all measures of aggregate productivity, and their associated analysis of reallocation, can be mapped into either aggregate GDP or welfare. While we are primarily interested in documenting the performance of one industry, the U.S. steel industry, we do so using an intuitive and frequently used set of decompositions. At the core of the concerns raised by PL is that the Olley-Pakes style aggregate productivity and the associated reallocation, do not evaluate the use of inputs at their marginal products. In the extreme case, if the marginal products of all inputs are equated across plants and, hence, in the absence of any frictions or wedges between marginal products and input prices, there cannot be any role for reallocating resources to more-productive plants.

In order to deal with this potential concern, we closely follow Petrin and Levinsohn (2012)'s approach to creating alternative decompositions of productivity growth.[54] We first cast our decomposition into the PL framework and discuss the measurement and implementation issues. Finally, we compute the PL decomposition and verify the robustness of our main results, rather than pursuing a detailed analysis of when and why these decompositions yield different results.[55]

6.3.1 Comparing both measures

The setup of PL is quite general, and we start by introducing the specifics of our application. First, we rely on a Cobb-Douglas production, which implies that output elasticities for each input are constant across plants and time, much like the application considered by PL.

A thorny issue is the treatment of capital. While PL work out the case for all inputs, in practice, we face the challenge of how to measure the user cost of capital. If we ignore the contribution of capital

[54]We rely on PL's code downloaded from `http://www.econ.umn.edu/~petrin/programs.html`, accessed August 30, 2013.

[55]The specific comparison with Olley-Pakes type decompositions has been done carefully and in great length by PL and subsequent work Nishida et al. (2013b,a).

stock to aggregate productivity growth (APG hereafter), this will bias our results, both because capital stock changed dramatically in this industry, and because vertically integrated plants and minimills have different capital intensities. Thus, we treat labor and capital as inputs into production in our PL-style productivity decompositions.[56]

Starting from PL's equation (9) on page 711, and letting h index our inputs (l, k), we multiply and divide by total revenue in the industry ($\sum_i P_i Q_i$), yielding aggregate productivity growth between $t-1$ and t as:

$$\begin{aligned} APG_t &= \sum_i \frac{P_i Q_i}{\sum_i P_i Q_i} \frac{\sum_i P_i Q_i}{\sum_i VA_i} \Delta\omega_{it} + \sum_i \frac{P_i Q_i}{\sum_i P_i Q_i} \frac{\sum_i P_i Q_i}{\sum_i VA_i} \sum_h (\beta_h - s_{ih}) \Delta h_{it} \\ &= \underbrace{\theta \sum_i ms_i \Delta\omega_{it}}_{TE} + \underbrace{\theta \sum_i ms_i \sum_h (\beta_h - s_{ih}) \Delta h_{it}}_{RE}, \end{aligned} \tag{17}$$

where all variables without a subscript it are approximated with the midpoint between their values at times t and $t-1$, and $\theta \equiv \frac{\sum_i P_i Q_i}{\sum_i VA_i}$ (Domar weight for the steel industry), and $\Delta h_{it} = \ln h_{it} - \ln h_{it-1}$ where lower cases denote logs.

The second line of equation (17) shows that APG can be decomposed into a Technical Efficiency (TE) component and a reallocation component (RE). The TE term is our plant improvement component in equation (15) up to a scaling by θ. This rescaling will not affect our analysis of the share of productivity growth coming from reallocation versus technical efficiency.[57]

Given our previous analysis, we can already say a lot about the various components in the PL decomposition in equation (17). First, while materials can be thought of as a flexible input that is free from any frictions, we do allow for an imperfectly competitive output market. This imperfect competition is plausible given the positive markups we found in Section 5.5.1. Thus, we should expect there to be a wedge between an input's output elasticity and the revenue share. For materials, our variable input, the markup drives a wedge between the material revenue share and the firm's output elasticity. Second, for labor and capital, which we allow to face adjustment costs, this wedge will be non-zero, irrespectively of whether there is imperfect competition in either the output or the input market.[58] This implies that there is the potential for the reallocation term in the PL framework to lead to aggregate productivity growth: The movement of inputs across producers with different markups and adjustment costs is a clear potential mechanism. Finally, from the raw data, as presented in Table 1 and Figure 1, we know that total employment dropped dramatically over the sample period, from 500,000 to 100,000. Moreover, the drop was almost entirely at integrated plants. Therefore, we expect an important role of labor in when we break down the PL-reallocation term into the labor and capital.

[56] This implies that we need to insert a user cost of capital to measure the share of the expenditure on capital in total value added. We use a value of 12 percent and verify the robustness of our results using different values.

[57] There is also a slight difference between our plant improvement term and PL due to the discrete nature of the data. In PL, the midpoint of market share is used, while we rely on the lagged value.

[58] See an extensive discussion of the wedge for inputs with adjustment costs, and their welfare implications in a dynamic context, in Asker et al. (2013).

6.3.2 Robust role of technology

To compute the APG for the industry, the left-hand side of equation (17), we need to deal with various implementation issues. First, we know that there is substantial entry and exit across plants of different technologies. Second, we need to approximate the continuous-time setup of PL to a discrete-time analogue. In addition, plant-specific cost shares are inherently noisy.[59] This leads us to the following equation that we take to our data:[60]

$$APG_t = \Delta \ln(\sum_i VA_{it}) - \sum_{L,K} \left[\sum_{i \in \mathcal{A}} \overline{a}_i^H \Delta h_{it} + \sum_{i \in \mathcal{B}} a_{it}^H - \sum_{i \in \mathcal{C}} a_{it-1}^H \right] \tag{18}$$

where a_i^H is the share of an input H's expenditure in the industry's total output VA (value added) with $H = \{L, K\}$ the input in levels, and $\mathcal{A}$, $\mathcal{B}$ and $\mathcal{C}$ denotes continuers, entrants, and exiters, respectively. The reallocation term RE is then simply recovered using the identity: $RE_t = APG_t - TE_t$.

Table 13 presents the PL-decomposition of Aggregate Productivity Growth, for both the entire industry, and separately for minimills and vertically integrated plants. We show both the total productivity growth in the steel industry (APG), as well as the shares accounted for by technical efficiency (TE), and reallocation (RE). We also present the components of reallocation that can be attributed to the reallocation of labor and capital. In the bottom panel of Table 13, we also reproduce the share of productivity growth accounted for by the within and covariance terms in the Olley-Pakes decomposition.

PL's measure of APG for the steel industry is 59 percent, while in our prior analysis, we found aggregate productivity growth of 22 percent. These numbers may appear to be incompatible, but it is important to notice that PL use a value-added metric for productivity, while we have employed a gross-output measure. Since the Domar weight for the steel industry (the ratio of output to value added) is about 2.5, this explains the discrepancy between these two measures of productivity growth.

The PL decomposition finds that 67 percent of productivity growth can be accounted for by technical efficiency, while the remaining 33 percent is due to reallocation. Our previous Olley-Pakes decompositions allocated 71 percent of productivity growth to the within component and 29 percent to the covariance term. Thus, it seems that, for our industry, the two approaches agree as to the role of reallocation of resources in explaining aggregate productivity growth. Indeed, once we account for sampling error in output elasticities β, we find overlapping 95-percent confidence intervals for these decompositions.

Likewise, once we drill down to the technology level, we also find a similar share of productivity growth accounted for by within-plant effects and reallocation between plants by the PL and Olley-Pakes approaches. For vertically integrated plants, the TE component is 74 percent, while the within component is 83 percent. For minimills, these numbers are 57 percent and 55 percent, respectively.

[59] See the discussion in De Loecker and Warzynski (2012) on the need to correct the *revenue shares* as the raw data might, for instance, lead to the wage bill over sales to lie anywhere from zero to a very large number. These plant-level shares are interacted with plant-level changes in input use, and this noise in revenue shares can have large implications.

[60] See Section 7 in PL on the specifics of the discrete-time approximation for more detail on the derivation of this equation.

When applying the PL decomposition by technology, we find that the reallocation component for integrated producers is substantial and that the labor term is large and negative at -26 percent. To understand this effect, note that with a positive markup, any reduction in total output will be damaging in terms of efficiency, as the market power induced quantity distortion is further accentuated. Thus, even if the labor share s_{li} and the output elasticity of labor β_l are identical across all plants, when labor falls among vertically integrated plants, this shows up as a negative reallocation term. Likewise, there is a positive labor reallocation term for minimills of 11 percent, since minimills expanded their workforce over the time period.

This logic does not directly translate to inputs that face substantial adjustment costs, such as capital, where the wedge contains both markups and adjustment costs. We find that the capital accounts for 13 percent of APG, indicating that capital reallocation had a large role in efficiency gains for the industry. We refer the reader to PL for a more thorough discussion of the interpretation of the capital reallocation component.

Finally, just as in our previous discussion of static decompositions of productivity growth, we know that plant entry and exit will confound the interpretation of the within and reallocation terms. This is equally true of our PL decompositions, but given the continuous time approximation, we do not pursue this analysis, and we appeal to our previous results on the importance of entry and exit.

7 Conclusion

There is, by now, extensive evidence that reallocation of resources across producers substantially impacts productivity growth. This paper is one of the first to provide a specific mechanism underlying such reallocation: The entry of a new technology, the minimill, and its associated increased competition, were largely responsible for the massive productivity growth in the U.S. steel industry.

We provide evidence that technological change can, by itself, bring about a process of resource reallocation over a long period of time and lead to substantial productivity growth for the industry as a whole. We find that the introduction of a new production technology spurred productivity growth through two channels.

First, the entry of minimills led to a slow but steady drop in the market share of the incumbent technology – the vertically integrated producers. As minimills were 7.5-percent more productive, this movement of market share between technologies was responsible for a third of the industry's productivity growth. Second, the old technology had faster growth in productivity than the new technology, with TFP growth of 24 percent for vertically integrated producers versus only ten percent for minimills. This catching-up process of the incumbents came about from a large *within* reallocation of resources among vertically integrated plants.

The reallocation among vertically integrated plants was largely due the exit of inefficient producers active in the low-quality segment (bar products.) On the other hand, minimills' productivity increased gradually over time due to a shift in the production function for all minimill producers. Although the first mimimill producing at a commercial level, entered in the late 1950s, the productivity effects were long-lasting and still affect the industry's performance today. In fact, the recent trend in market shares suggests that minimills have started to enter the high-quality segment of the industry – sheet products – and taking our results at face value would indicate that more substantial productivity gains can be expected.

Our results indicate that the arrival of new technologies can have a major impact on productive efficiency through increased competition and its associated reallocation of economic resources, leading to an increase in the industry's overall performance. It is critical to obtain measures of plant-level performance and technology to identify this mechanism – i.e., without indicators of technology at the plant level, we would falsely attribute the productivity gains to other factors correlated with aggregate productivity, such as international competition, geography, and a variety of firm-level characteristics.

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TABLES AND FIGURES

Table 1: Relative Performance of the Steel Sector

	Steel Sector	Mean Sector	Median Sector
Δ TFP	28%	7%	3%
Δ Shipments	-35%	60%	61%
Δ Labor	-80%	-5%	-1%
Δ Materials	-41%	45%	39%
Δ Value Added	-43%	34%	38%
Δ Price†	-23%	-2%	-3%
Δ Material Price†	-10%	-11%	-9%

Source: NBER-CES Dataset for SIC Code 3312. Note: Only sectors over 10 billion dollars are included. Changes computed between 1972-2002. † Material and Output prices indexes are deflated by the GDP deflator.

Table 2: Entry and Exit in U.S. Steel

	Entrant Market Share (Plants)	Exitor Market Share (Plants)
1963-1972	6 (29)	9 (D∗)
1973-1982	5 (49)	20 (20)
1983-1992	21 (55)	18 (47)
1993-2002	12 (30)	2 (41)
Minimills	Entrants	exiters
1963-1972	17	D∗
1973-1982	39	0
1983-1992	43	26
1993-2002	D∗	17
Vertically Integrated	Entrants	exiters
1963-1972	12	D∗
1973-1982	10	20
1983-1992	12	21
1993-2002	D∗	24

Note: D∗ cannot be disclosed due to the small number of observations. Numbers refer to the revenue market share represented by exiters and entrants, while numbers in parenthesis refer to the count of plants that enter or exit.

Table 3: Production Functions: Minimills versus Vertically Integrated Plants

	OLS		GMM	
	Pooled	Tech-specific	Pooled	Tech-specific
	I	II	III	VI
Material	0.608***	0.614***	0.680***	0.657***
	(0.034)	(0.032)	(0.022)	(0.026)
Labor	0.335***	0.306***	0.274***	0.261***
	(0.028)	(0.023)	(0.020)	(0.022)
Capital	0.043	0.056	0.079***	0.097***
	(0.037)	(0.029)	(0.016)	(0.022)
Material $\times$ VI		-0.029		0.059
		(0.063)		(0.047)
Labor $\times$ VI		0.072		0.008
		(0.049)		(0.042)
Capital $\times$ VI		-0.031		-0.034
		(0.023)		(0.030)
Year FE	X	X		
R^2	0.966	0.966		
F-Stat	1663.267	1426.796		
Plants	1498	1498	1498	1498

Note: VI is a dummy variable equal to one if a plant is a vertically integrated producer.

Table 6: International Competition: Comparing the Steel Sector to U.S. Manufacturing

	Change Total Imports		
Period	Steel	Average	Median
% Δ [72-02]	4.1	66.1	23.7

	Import Penetration Rate		
Year	Steel	Average	Weighted Average
1972	0.099	0.066	0.055
1996	0.180	0.220	0.157
Change	0.081	0.154	0.102
% Change	81	233	85

Note: The average and weighted average are computed over all available four-digit SIC87 industries using data provided by the NBER Manufacturing Database (for shipment data) and Bernard et al. (2006) (for import penetration data). The changes are computed by industry before taking averages. The import penetration rate data are available only up to 1996. Weights are based on the industry's share of shipments in total manufacturing shipments as recorded in the NBER Manufacturing Database.

Table 4: Production Function Coefficients and Technology Premium

	Input and Output Price Deflators		No Plant-Level Output Price Deflator		No Plant-Level Input Price Deflator	
	GMM	OLS	GMM	OLS	GMM	OLS
	I	II	III	IV	V	VI
Material	0.680	0.631	0.650	0.610	0.680	0.631
	[0.65 0.73]	*[0.58 0.69]*	*[0.62 0.70]*	*[0.52 0.67]*	*[0.64 0.73]*	*[0.58 0.69]*
Labor	0.274	0.327	0.282	0.332	0.273	0.327
	[0.24 0.31]	*[0.28 0.37]*	*[0.24 0.32]*	*[0.29 0.38]*	*[0.24 0.31]*	*[0.28 0.37]*
Capital	0.079	0.050	0.082	0.051	0.082	0.050
	[0.04 0.11]	*[-0.01 0.10]*	*[0.05 0.11]*	*[-0.01 0.10]*	*[0.05 0.11]*	*[-0.01 0.10]*
VI premium	-0.075	-0.018	-0.038	0.013	-0.076	-0.018
	[-0.12 -0.04]	*[-0.04 0.00]*	*[-0.08 0.00]*	*[-0.01 0.03]*	*[-0.12 -0.04]*	*[-0.04 0.00]*

Note: 95-percent confidence in parenthesis. GMM indicates that a two-stage investment control function procedure with a selection adjustment was used. VI premium is calculated by projecting estimated productivity on an indicator for a vertically integrated plant, along with year dummies. Standard errors are clustered at the plant-level to control for heteroskedasticity and serial correlation. For GMM columns, this clustering is computed via block bootstrap, which, in addition, corrects for the multi-step nature of the GMM estimator.

Table 5: Technology Premium: Robustness Checks

	Dependent Variable : Productivity ω			
	I	II	III	IV
VI	-0.074**	-0.084	-0.102***	-0.178*
	(0.024)	(0.048)	(0.020)	(0.074)
Fixed Effect				
Year	X			
Year-Firm		X		
State-Year			X	
Firm-Year-State				X
Observations	1498	1498	1498	1498
Groups	301	914	289	1291
R^2	0.052	0.005	0.021	0.027
F	15.220	3.006	25.373	5.730

Note: The standard errors are clustered at the plant-level. VI indicates Vertically Integrated plants.

Table 7: Static Decompositions of Productivity Growth (Change 1963-2002)

Aggregate TFP $\Delta\Omega$	22.1%	
Olley-Pakes Decomposition:		
Unweighted Average: $\Delta\overline{\omega}$	15.7% (0.71)	
Covariance: $\Delta\Gamma^{OP}$	6.4% (0.29)	
Between Decomposition:		
Unweighted Average: $\Delta\overline{\overline{\Omega}}$	17.0 % (0.77)	
Between Covariance: $\Delta\Gamma^{B}$	5.1 % (0.23)	
Within Decomposition:	Minimills	Integrated
Aggregate TFP: $\Delta\Omega(\psi)$	9.6%	24.3%
Unweighted Average: $\Delta\overline{\omega}(\psi)$	5.4% (0.55)	18.4% (0.83)
Within Covariance: $\Delta\Gamma^{OP}(\psi)$	4.4% (0.45)	3.7% (0.17)

Note: The share of each component in the total aggregate productivity growth is listed in parentheses.

Table 8: Dynamic Decomposition of Productivity Growth

Component	All	Minimill	Integrated
Total Change	22.1%	9.6%	24.3%
		(0.28)	(0.49)
Plant Improvement	9.5%	11.8%	9.3%
		(0.34)	(0.19)
Reallocation	9.3%	-0.3%	11.3%
		(-0.03)	(0.23)
Net Entry	3.3%	-2.0%	3.8%
		(-0.03)	(0.07)
Entry-Exit Premium		0.0%	4.4%

Note: The share of each component in the total aggregate productivity growth is listed in parentheses. See equation (15) for definitions of various terms. For example, the share of minimill productivity growth (9.6%) in aggregate productivity growth is given by: $9.6/17.7 \times 0.77 = 0.28$ – i.e., we compute the share of the minimill productivity growth in the unweighted aggregate productivity growth term, which we know from the top panel is 0.77.

Table 9: Sheet Productivity Premium

	Dependent Variable: Productivity ω									
	Panel A: All Plants					Panel B: Vertically Integrated				
	I	II	III	IV	V	VI	VII	VIII	IX	X
Vertically Integrated	-0.080***	-0.082***	-0.115***	-0.089*	-0.199**					
	(0.021)	(0.024)	(0.018)	(0.036)	(0.077)					
Sheet Specialization		0.073*	0.094***	0.119**	0.078	0.058	0.099**	0.114*	0.168*	0.089
Ratio		(0.035)	(0.025)	(0.036)	(0.068)	(0.038)	(0.032)	(0.047)	(0.084)	(0.079)
Fixed Effects										
Year	X	X				X			X	
State-Year			X				X			
Firm-Year				X				X		
Firm-State-Year					X					X
Plant									X	
Observations	1498	1498	1498	1498	1498	667	667	667	667	667
Number of FE	301	301	289	914	129	124	175	353	124	540
R^2	0.020	0.082	0.034	0.024	0.033	0.069	0.019	0.019	0.081	0.011
F	14.639	17.167	21.143	7.019	3.537	7.944	9.290	5.980	5.214	1.263

Note: Standard Errors clustered by plant, but not corrected for the sampling error in constructed productivity. Sheet Specialization Ratio is the share of revenues accounted for by sheet products (hot and cold rolled sheet).

Table 10: Determinants of Exit

	Dependent Variable: Plant Exists in 2002				
	Panel A: All Plants		Panel B: Vertically Integrated		
	I	II	III	IV	V
Vertically Integrated	-0.36***	-0.39***			
	(0.09)	(0.08)			
Sheet Specialization Ratio	0.39**	0.36*	0.31*	0.31*	0.22
	(0.14)	(0.14)	(0.13)	(0.13)	(0.14)
Log Capital (k)		0.02		0.20	0.24
		(0.03)		(0.24)	(0.25)
Productivity (ω)		0.03			0.05
		(0.14)			(0.04)
Observations	128	128	78	78	78
Log-Likelihood	-73.88	-73.72	-40.36	-40.02	-39.24
$\chi 2$	16.97	17.30	5.89	6.58	8.12
Baseline Probability	0.33	0.33	0.23	0.23	0.22

Note: Marginal Effects presented. Dependent variable is whether the plant has not exited by 2002 given its status in 1963. Very similar results are found with 1972 and 1977 as base years.

Table 11: Static Decompositions under Alternative Productivity Measures

	Baseline I	OLS II	No Material Price Deflator III	No Output Price Deflator IV	Tech-Specific Production Function V
Change in TFP	22%	28%	22%	23%	19%
	[0.17 0.27]	*[0.23 0.33]*	*[0.16 0.27]*	*[0.18 0.28]*	*[0.01 0.27]*
Olley-Pakes					
Unweighted Average ($\Delta\overline{\omega}$)	71%	69%	71%	77%	65%
	[0.59 0.79]	*[0.62 0.73]*	*[0.60 0.79]*	*[0.68 0.84]*	*[-0.01 0.87]*
Covariance ($\Delta\Gamma^{OP}$)	29%	32%	29%	23%	36%
	[0.21 0.41]	*[0.27 0.38]*	*[0.21 0.41]*	*[0.16 0.32]*	*[0.14 1.01]*
Between					
Change in $\overline{\Omega}$	77%	90%	76%	82%	81%
	[0.68 0.83]	*[0.86 0.94]*	*[0.68 0.83]*	*[0.74 0.87]*	*[0.52 2.50]*
Change in Between Technology	23%	10%	24%	18%	19%
Covariance ($\Delta\Gamma^{B}$)	*[0.17 0.32]*	*[0.06 0.14]*	*[0.17 0.33]*	*[0.13 0.26]*	*[-1.50 0.49]*
Within Technology					
Minimills					
Change in TFP	43%	74%	42%	50%	45%
(ratio to aggregate $\frac{\Delta\Omega(MM)}{\Delta\Omega}$)	*[0.19 0.60]*	*[0.59 0.85]*	*[0.18 0.58]*	*[0.29 0.63]*	*[0.02 1.85]*
Fraction from Unweighted Average	55%	62%	55%	77%	55%
($\Delta\overline{\omega}(MM)$)	*[-0.02 0.70]*	*[0.53 0.69]*	*[-0.05 0.70]*	*[0.59 0.86]*	*[-0.05 0.77]*
Fraction from Covariance	45%	38%	45%	24%	45%
($\Delta\Gamma^{OP}(MM)$)	*[0.31 1.02]*	*[0.31 0.47]*	*[0.30 1.05]*	*[0.14 0.41]*	*[0.23 1.05]*
Vertically Integrated					
Change in TFP	110%	107%	111%	114%	118%
(ratio to aggregate $\frac{\Delta\Omega(VI)}{\Delta\Omega}$)	*[1.03 1.21]*	*[1.01 1.14]*	*[1.03 1.22]*	*[1.06 1.24]*	*[0.78 3.24]*
Fraction from Unweighted Average	83%	76%	84%	89%	87%
($\Delta\overline{\omega}(VI)$)	*[0.73 0.94]*	*[0.71 0.82]*	*[0.74 0.94]*	*[0.81 0.98]*	*[0.73 1.02]*
Fraction from Covariance	17%	24%	17%	11%	13%
($\Delta\Gamma^{OP}(VI)$)	*[0.06 0.27]*	*[0.18 0.30]*	*[0.06 0.26]*	*[0.02 0.19]*	*[-0.02 0.27]*

Note: GMM refers to the Olley-Pakes control function approach. Plant-level output prices refers to deflating revenue using product-level price indexes. Plant-level material prices refers to deflating material inputs costs using material specific price indexes. Bootstrapped 95-percent confidence intervals using 10,000 replications are shown in brackets, and these include only sampling error in the computation of productivity ω.

Table 12: Dynamic Decompositions under Alternative Productivity Measures

	Baseline	OLS	No Material Price Deflator	No Output Price Deflator	Tech-Specific Production Function
	I	II	III	IV	V
Dynamic Decomposition					
All					
Plant Improvement	43%	46%	43%	49%	47%
	[0.35 0.49]	*[0.40 0.50]*	*[0.34 0.49]*	*[0.43 0.53]*	*[0.20 1.15]*
Reallocation	42%	42%	42%	40%	43%
	[0.35 0.54]	*[0.37 0.49]*	*[0.35 0.54]*	*[0.33 0.49]*	*[0.30 0.83]*
Entry-Exit	15%	12%	15%	11%	10%
	[0.12 0.18]	*[0.11 0.13]*	*[0.12 0.18]*	*[0.08 0.14]*	*-[0.85 0.29]*
Minimills					
Plant Improvement	123%	87%	125%	136%	124%
	[0.94 2.59]	*[0.77 1.03]*	*[0.94 2.68]*	*[1.07 2.36]*	*[0.88 2.59]*
Reallocation	-3%	5%	-3%	-11%	9%
	-[0.51 0.09]	*-[0.03 0.12]*	*-[0.54 0.09]*	*-[0.49 0.01]*	*-[0.56 1.03]*
Entry-Exit	-21%	8%	-22%	-25%	-34%
	-[1.08 0.00]	*-[0.02 0.14]*	*-[1.18 -0.01]*	*-[0.87 -0.07]*	*-[1.92 0.04]*
Vertically Integrated					
Plant Improvement	38%	40%	38%	42%	39%
	[0.26 0.48]	*[0.33 0.46]*	*[0.26 0.48]*	*[0.32 0.51]*	*[0.09 0.49]*
Reallocation	46%	54%	46%	46%	51%
	[0.33 0.61]	*[0.47 0.61]*	*[0.32 0.61]*	*[0.34 0.59]*	*[0.32 1.15]*
Entry-Exit	16%	7%	16%	12%	11%
	[0.10 0.22]	*[0.05 0.09]*	*[0.11 0.22]*	*[0.07 0.17]*	*-[0.35 0.29]*

Note: GMM refers to the Olley-Pakes control function approach. Plant-level output prices refers to deflating revenue using product-level price indexes. Plant-level material prices refers to deflating material inputs costs using material specific price indexes. Bootstrapped 95-percent confidence intervals using 10,000 replications are shown in brackets, and these include only sampling error in the computation of productivity ω.

Table 13: Alternative Decomposition

Sample	APG	Technical Efficiency (TE)	Reallocation (RE)	Labor RE	Capital RE
Steel	0.59	67%	33%	-16%	13%
Vertically Integrated	0.59	74%	28%	-26%	23%
Minimill	0.61	57%	46%	11%	-20%

Main Results from Table 7: Within and Reallocation

Sample	Within	Covariance
Steel	71%	29%
Vertically Integrated	83%	17%
Minimill	55%	45%

Note: All entries in the table, except for APG, are percentage shares of APG.

Figure 1: Evolution of the Steel Industry, and Vertically Integrated Mills and Minimills

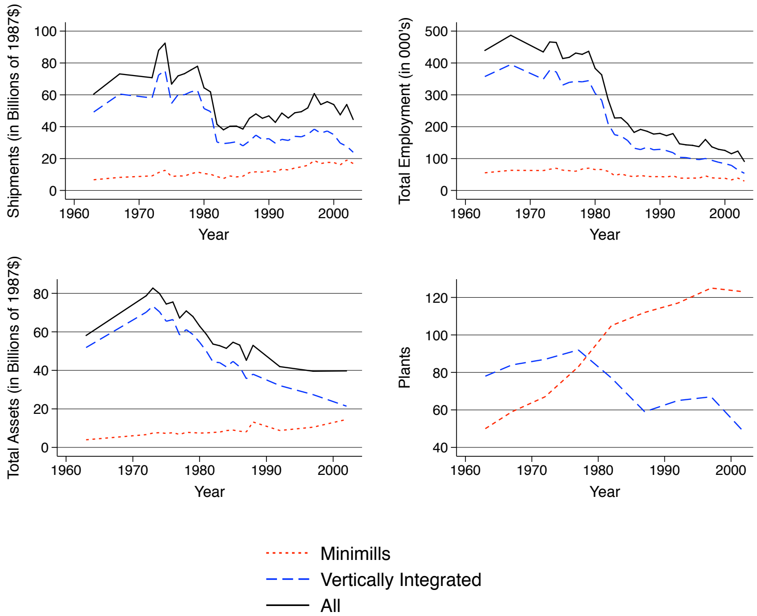


Figure 2: Minimills Market share by Major Product.

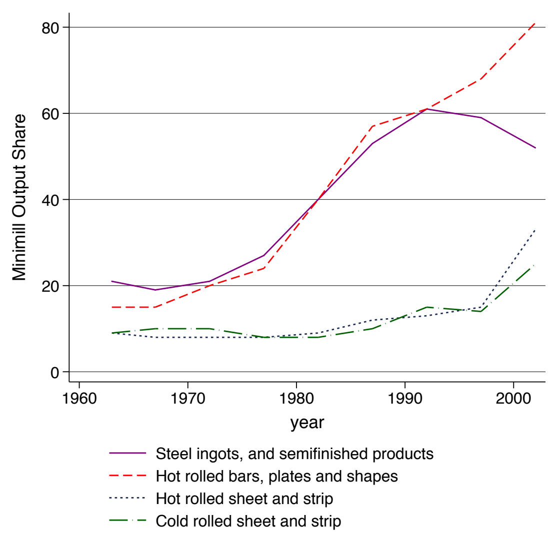
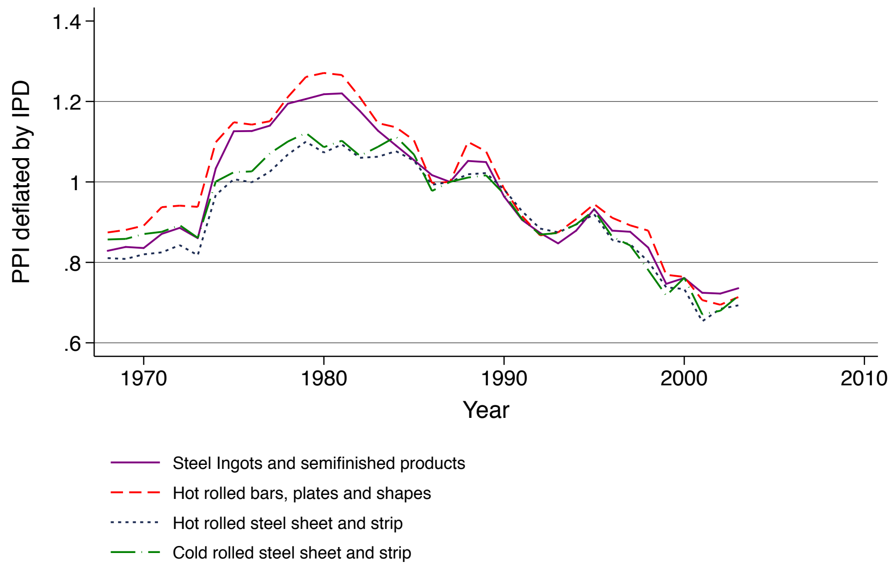
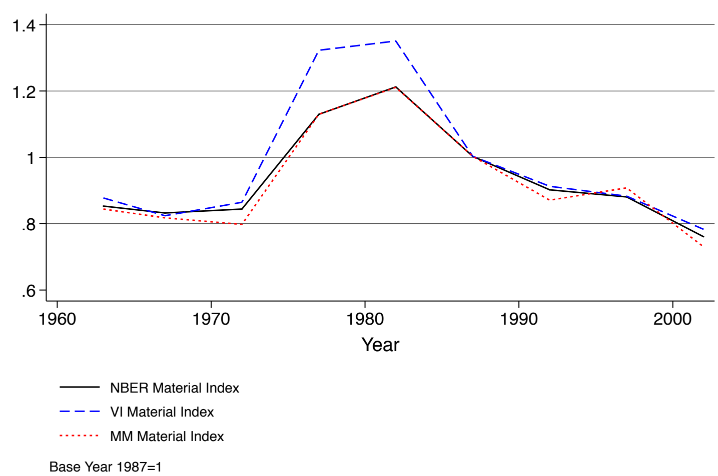


Figure 3: Producer Output and Input Price Indexes

Panel A: Output Price Index by Product Segment

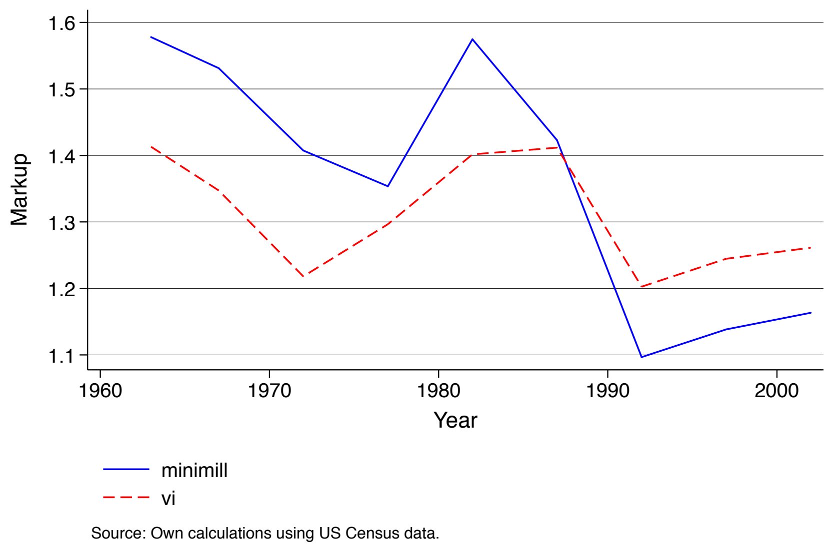


Panel B: Input Price Index by Technology



Note: Producer Price Index for Selected Steel Products deflated by GDP Deflator. Material Price Index deflated by GDP Deflator. Base year 1987=100. Source: BLS and Authors calculations.

Figure 4: Market Share Weighted Markups



Online Appendix for Reallocation and Technology:
Evidence from the U.S. Steel Industry

Allan Collard-Wexler and Jan De Loecker
NYU and NBER, and Princeton University, NBER and CEPR

December 19, 2013

A Data Appendix

A.1 Sample Selection

We pull all plants in the Census of Manufacturing, Annual Survey of Manufacturing and Longitudinal Business Database from 1963 to 2007 coded in either NAICS 33111 or SIC 3312 at some point in their lives.

The Longitudinal Business Database has worse industry coding than the Census of Manufacturing, and taking its coding literally introduces a large number of non-steel mills into the sample.[61] Therefore, we include a plant in the sample only if it has been coded in steel in either the CMF or the ASM.

A.2 Coding Minimills, Vertically Integrated, and Rolling Plants

A primary issue in understanding the Steel industry is how to code plants as being minimills, vertically integrated or rolling and processing plants. For references on the differences between minimills and vertically integrated plants and the production process for steel, see Fruehan (1998) p.1-12 and Crandall (1981) p.5-15.

The 2007, 2002 and 1997 Census of Manufacturing have a special inquiry questionnaire for the steel industry (SI) appended to it. This questionnaire asks plants if they are considered a minimill or not. Moreover, the SI also asks for plant hours in electric arc furnaces, blast furnaces, coke ovens, and basic oxygen furnaces. If a plant reports plant hours in coke, blast, or basic oxygen furnace, we flag this plant as a vertically integrated plant, since vertically integrated plants are defined by the production process that first produces pig iron and slag, and then processes the result in a basic oxygen furnace. If a plant reports being a minimill or if it reports hours in an electric arc furnace, then we code this plant as a minimill.

Some vertically integrated plants occasionally have electric arc furnaces. Whenever a plant report hours in an electric arc furnace and in a basic oxygen or blast furnace, we assign this plant to the vertically integrated category. The reason is that the vertically integrated section of the plant is usually far bigger than the electric furnace section.

Many plants do not report hours in any steel mill department, and do not report being minimills either. We call these plants rolling mills or processors, as they do not produce steel per se, but process steel products. For instance, a rolling mill might use steel ingots, blooms and billets (steel shapes), and roll these into steel sheet. Alternatively, a mill might take steel rods and shape them into steel screws.

For plants that were still in operation in 1997, or were built after 1997, the SI file is all we need to identify the plant's type. However, for plants that shut down pre-1997, we use the material and product trailer to the Census of Manufacturing to classify them.

Minimills can be identified by their input use. Electric arc furnaces use a combination of scrap steel and direct-reduced iron as inputs. Thus, if a plant uses any direct-reduced iron, we flag this plant as a minimill. Likewise, if scrap steel represents more than 20 percent of a plant's material use, we flag this plant as a minimill.[62]

Vertically integrated plants can also be identified from their input use. If a plant uses "Coal for Coke", this is a good indication that a plant has a blast furnace. We flag rolling mills by their use of "Steel Shapes and Forms" – steel ingots and so on that are shaped into steel products.

[61] In particular, the Zip Business Patterns database, that uses the same underlying source as the LBD, has a large number of entrants coded in NAICS 33111 from 1997 to 2002 that are not steel mills.

[62] Basic oxygen furnaces at vertically integrated plants also can a take a small percent of scrap steel. For this reason, we flag a plant as a minimill only if scrap steel is a large part of their inputs.

We also use the product trailer to categorize plants. If a plant produces “Coke Oven or Blast Furnace Products”, we flag this plant as vertically integrated. In addition, if a plant produces “Cold Rolled Sheet Steel” before 1980, we flag this plant as vertically integrated, as minimills only started producing cold rolled sheets in the mid-80s. For references on the changing ability of minimills to produce sheet products, see Rogers (2009) on page 162 and chapter 8 of Hall (1997).

Plants are not always consistently coded as either minimills, vertically integrated, or rolling mills from one year to another. Thus, we classify a plant based on its history of such flags. Specifically, a plant is vertically integrated if it is flagged as such at least 80 percent of the time. Likewise, a plant is assigned to the minimill category if it is flagged as such at least 80 percent of the time.

Since vertically integrated plants, as their name suggests, are typically engaged in multiple activities, such as having an electric arc furnace and a basic oxygen furnace, along with a rolling mill, we first flag plants as vertically integrated or not, then flag the remaining plants as minimills. Leftover plants are assigned to be rolling mills.

A.3 Coding Products

We use the product trailer of the Census Bureau to investigate the products produced by steel producers. We categorize products into the following types which are responsible for 93 percent of output not categorized as “other” or “unclassified” in 1997: Hot-Rolled Steel Bar: SIC 33124, NAICS 3311117; Hot Rolled Sheet and Strip: SIC 33123, NAICS 3311115; Cold Rolled Sheet and Strip: SIC 33127, SIC 33167, NAICS 3312211, NAICS 3312211D; Cold Finished Bars and Bar Shapes: SIC 33128, SIC 33168, NAICS 3312213, NAICS 331111F; Steel Ingots and Semi-Finished Shapes: SIC 33122, NAICS 3311113; Steel Wire: SIC 33125, SIC 33155, NAICS 3312225, NAICS 3311119; Steel Pipe and Tube: SIC 33170, SIC 33177, NAICS 3312100, NAICS 331111B.

B Additional Tables and Figures

Table B.1: Summary Statistics for Minimills and Vertically Integrated Producers

Vertically Integrated

	Mean	**Std. Dev.**	**Observations**
Shipments†	647	671	2,192
Value Added†	261	311	2,192
Cost of Materials†	343	369	2,192
Investment†	36	63	2,192
Assets†	690	860	1,525
Workers	3,062	3,721	2,192
Wage Per Hour	25	8	2,192

Minimills

	Mean	**Std. Dev.**	**Observations**
Shipments†	153	178	2,687
Value Added†	61	80	2,687
Cost of Materials†	85	112	2,687
Investment†	7	17	2,687
Assets†	103	139	1,705
Workers	633	750	2,687
Wage Per Hour	25	9	2,687

Note: † In millions of 1997 dollars. The number of observations for total assets is smaller since these are not part of the ASM after 1992.

Table B.2: Differences between Minimills and Vertically Integrated Plants

Plant-level characteristic	Premium for VI Plants					
	All	1963	1972	1982	1992	2002
Shipments	1.44	1.60	1.60	1.46	1.32	1.02
	(0.08)	(0.27)	(0.25)	(0.23)	(0.23)	(0.26)
Value Added	1.32	1.43	1.33	1.23	1.31	0.97
	(0.09)	(0.30)	(0.26)	(0.24)	(0.25)	(0.28)
Assets	1.68	2.11	1.88	1.88	1.46	1.17
	(0.10)	(0.32)	(0.29)	(0.27)	(0.28)	(0.31)
Cost of Materials	1.57	1.88	1.74	1.70	1.34	1.04
	(0.08)	(0.28)	(0.25)	(0.23)	(0.24)	(0.26)
Employment	1.24	1.37	1.30	1.32	1.20	0.97
	(0.08)	(0.26)	(0.24)	(0.22)	(0.22)	(0.25)
Shipment per worker	0.20	0.23	0.25	0.14	0.12	0.05
	(0.03)	(0.10)	(0.09)	(0.08)	(0.08)	(0.10)
Value Added per worker	0.08	0.06	0.03	-0.09	0.12	0.00
	(0.04)	(0.13)	(0.11)	(0.10)	(0.11)	(0.12)
Wage	0.06	0.04	0.07	0.14	0.00	0.07
	(0.01)	(0.05)	(0.04)	(0.04)	(0.04)	(0.04)

Note: Estimates display the log of the ratio of the mean for VI plants over the mean for MM plants. Thus, 1.44 in the top left cell indicates that the average vertically integrated plant shipped 144 percent more than the average minimill or, equivalently, 4.2 times more, while a coefficient of 0 indicates that VI and MM plants have identical means. Year Controls included in each regression. There are a total of 1499 observations in these regressions.

Table B.4: Profit Differences: Minimills versus Vertically Integrated

Dependent Variable	Rate of Return on Capital		Profit Margin	
VI Premium	-0.175***	-0.187***	-0.019*	-0.040***
	(0.024)	(0.023)	(0.009)	(0.009)
Year FE		X		X
Constant	0.492***	0.498***	0.280***	0.330***
	(0.016)	(0.039)	(0.006)	(0.015)
Observations	1355	1355	1355	1355

Note: Median regression presented. Profit Margin is defined as sales minus cost of materials and salaries over sales ($\frac{R-p^m M-wL}{R}$), and Rate of Return on Capital is defined as sales minus cost of materials and salaries over capital ($\frac{R-p^m M-wL}{K}$).

Table B.3: Production by Product

Year	HRS	HRB	CRS	Ingots	P&T	Blast	CFB	Wire	Other
1963	23	23	16	13	7	5	1	2	9
1967	21	23	14	13	7	5	1	2	14
1972	27	23	16	10	6	5	1	2	9
1977	26	22	17	10	8	7	1	1	8
1982	30	21	15	8	11	5	1	1	9
1987	38	20	17	8	5	3	1	1	7
1992	37	21	16	8	5	4	2	1	7
1997	35	21	17	7	6	4	2	1	7
2002	31	22	23	7	6	2	2	2	6

Note: Fraction of Industry Output Accounted for by each product: Hot-rolled steel sheet (HRS), Hot-rolled bar (HRB), Cold-rolled sheet (CRS), Ingots and shapes, Pipe and tube (P & T), Wire, Cold-finished bars (CFB), and coke oven and blast furnace products (Blast), Steel Wire (Wire). The one product whose shipments fall notably over this period is steel ingots and semi-finished shapes (SISS). However, SISS are used primarily in rolling mills to produce steel sheet and bar. Since the mid 1990's with the development of slab casting technologies, steel has been directly shaped into sheets at the mill.

Table B.5: Exit and Profits

Dependent Variable	Exit in Next 5 Years: 14% Probability		
Profit Margin	-0.159**		
	(0.052)		
Rate Return Capital		-0.045**	
		(0.016)	
Productivity			-0.059
			(0.034)
VI	0.113***	0.120***	0.119***
	(0.021)	(0.021)	(0.021)
Capital	-0.025***	-0.031***	-0.026***
	(0.005)	(0.005)	(0.005)
Year FE	X	X	X
Log-Likelihood	-407	-407	-410
χ^2	135	134	129
Observations	1184	1184	1184
Pseudo-R^2	0.142	0.141	0.136

Note: Marginal Effects from a Probit presented.

Table B.6: Comparison of Productivity Results in IPS and CWDL

	Paper	
	IPS 1999	CWDL 2013
Producers	19 Rolling Mills	301 Steel Mills
Years	5 years	1963-2002
Performance Measure	Up-Time	Gross Output TFP
Main Result	6.7%	30%
	Highest estimate	of which 2/3 minimill

Note: In order to compare IPS's findings to ours, we have to convert the 6.7 percent increase in up-time into a productivity number consistent with our gross-output production function framework. Note that under a Leontief or value-added production function, up-time is a direct estimate of the productivity increase (which seems plausible in the setting considered by IPS). To do this in our context we use the fact that material costs for the integrated mills in our sample are between 50 and 60 percent of costs. In other words, labor and capital are fixed in the short run (think of increasing capacity from a 20hrs/day to 24 hrs/ day) but materials will increase when capacity utilization goes up, an implication of an increase in up-time. This implies that productivity increased, due to better HR practice, by 2.7% and 3.35%. To get at this number we multiply $(1 - \beta_m) * 0.067$. This number sits very well with our results on within plant improvements at integrated mills (remember IPS has no minimill in the data).

Table B.7: Industry Productivity and Foreign Competition

Specification	Constant	Coefficient	Predicted TFP Steel	Share of Actual
All	0.07	0.11	0.081	0.34
(Obs: 385)	(0.03)	(0.13)		
Excl SIC=3674	-0.02	1.17	0.079	0.34
(Obs: 384)	(0.03)	(0.17)		
Big Sectors/Excl SIC=3674	-0.10	2.32	0.087	0.37
(Obs: 80)	(0.05)	(0.17)		

Note: We merged the NBER Manufacturing Database with the NBER U.S. Trade Database, using the 4-digit SIC87 (s) industry classification. We regress the change in aggregate productivity ($\Delta\Omega$), a long difference between 1972-1996, on the change in import penetration ratio. In particular we consider $\Delta\Omega_s = \gamma_0 + \gamma_1 \Delta IPR_s + \nu_s$. All regressions are weighted by the industry's share in total manufacturing shipments. Big sectors are defined as having USD 10 BLN or more in total shipments.

Table B.8: Unionization Rates

Year	Steel Union Membership	Manufacturing Union Membership
1983	0.60	0.25
1984	0.54	0.23
1985	0.55	0.23
1986	0.56	0.22
1987	0.52	0.21
1988	0.52	0.20
1989	0.51	0.19
1990	0.49	0.20
1991	0.46	0.19
1992	0.49	0.18
1993	0.52	0.18
1994	0.45	0.17
1995	0.46	0.15
1996	0.48	0.16
1997	0.41	0.15
1998	0.40	0.15
1999	0.40	0.15
2000	0.39	0.14
2001	0.40	0.13
2002	0.36	0.13

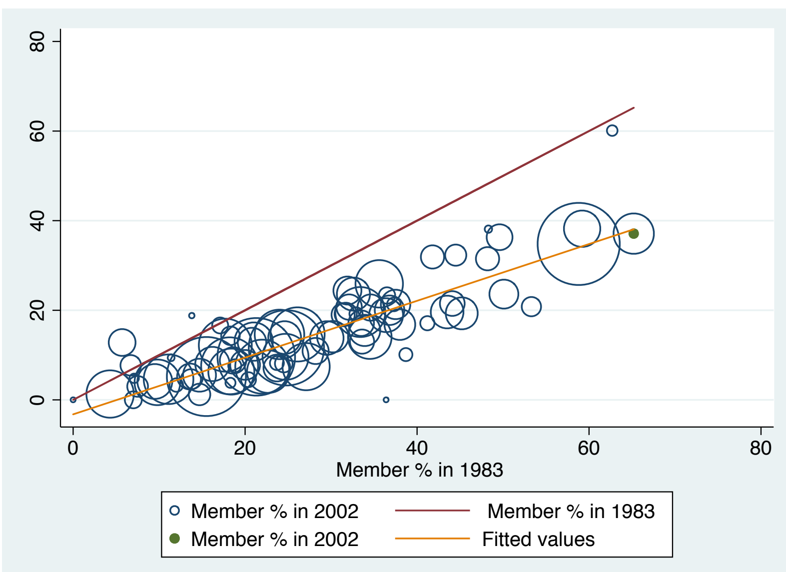
Note: The data are directly from the CPS database and was downloaded from `www.unionstats.com`.

Table B.9: Welfare effects under various demand elasticities

	$\epsilon = -0.6$	$\epsilon = -3.5$	$\epsilon = -1$
60% Fall in Prices Due to Minimills			
Change CS	9.3 Billion $	11.2 Billion $	9.5 Billion $
Share Change CS	13%	16%	13%
100% Fall in Prices Due to Minimills			
Change CS (All)	17 Billion $	23 Billion $	18 Billion $
Share Change CS (All)	24 %	33 %	25 %

Note: The different elasticities of demand are based on 1) an empirical study of U.S. steel by Maasoumi et al. (2002) , 2) the implied (averaged across time and plants) elasticity of demand from our markup estimates, and 3) an unit-elastic demand curve. Throughout our calculations we assume a linear demand curve. The consumer surplus is calculated as follows: $R63 * (1 - \Delta(P02, P63) * (1/2 + 1/2 * (1 + \Delta(P) * \epsilon))$ where $\Delta(P02, P63) = (1/(1 - \Delta P))$ and $\Delta P = -0.28 * \lambda$, and λ is either 0.6 or 1, depending on the case we consider – i.e., whether we attribute minimills to 60 percent or 100 percent of aggregate productivity growth. All changes in CS are reported in 1997 USD.

Figure B.1: Change in Union Membership 1983-2002: Steel and the rest of manufacturing



Note: We plot unionization membership rates of 1983 against those of 2002. Each observation is a 3-digit CIC industry, where the size of circle reflects the size in terms of employment of the industry. The red is the 45 degree line, while the yellow line indicates the line-of-best fit. The Steel Industry is represented by a full (green) circle. The data come from CPS (`www.unionstats.com`).

C Output and Input Deflators

Recovering productivity using revenue and expenditure data requires that we correct for potential price variation across plants and time, for both output and inputs. Below, we describe our procedure.

C.1 Output price deflator

In order to guarantee that we recover productivity, ω_{it}, using plant/product revenue data we rely on a plant-specific output deflator. We construct this deflator using product-level revenues at the plant level (recorded in the census data) in combination with product-level price data (from the BLS).[63]

To make sure that price variation – across plants and time – is fully controlled for, we assume the following structure: Plants charge the same markup across all their products, while markups can flexibly vary across plants and time. The heterogeneity in markups will naturally arise if plants are heterogeneous in their underlying productivity.

Before we derive the exact price deflator, we state explicitly what we observe in the data: revenues (R_{ijt}), input (X_{it}) and prices (P_{jt}).

We start out with the following production function:

$$Q_{ijt} = X_{ijt}\Omega_{it}, \tag{C.1}$$

where we are explicit about productivity only being plant-specific and not plant-product-specific. The input bundle X_{ijt} contains labor, intermediate inputs and capital, scaled by their corresponding technology parameters, $X = L^{\beta_l}K^{\beta_k}M^{\beta_m}$.

Now consider plant-level revenue, which is obtained by summing product-specific revenues, and using the production function:

$$R_{it} = \sum_j X_{ijt}\Omega_{it}P_{jt}. \tag{C.2}$$

To recover plant-level productivity from a regression of plant-level (deflated) revenues and input use, we use:

$$X_{ijt} \equiv s_{ijt}X_{it} \tag{C.3}$$

Plugging the last expression into the one for plant-level revenue, we get:

$$R_{it} = \Omega_{it}X_{it}\sum_j s_{ijt}P_{jt} \tag{C.4}$$

Up to s_{ijt}, which we will discuss below, everything is directly observable and, therefore, we can recover productivity using standard estimation techniques using:

$$\frac{R_{it}}{\sum_j s_{ijt}P_{jt}} = X_{it}\Omega_{it} \tag{C.5}$$

or in logs:

[63] Specifically, we use the following BLS price series: PCU331111331111: Steel; PCU3311113311111: Coke oven and blast furnace products; PCU3311113311113: Steel ingots and semifinished products; PCU3311113311115: Hot rolled steel sheet and strip; PCU3311113311117: Hot rolled steel bars, plates, and structural shapes; PCU3311113311119: Steel wire; PCU331111331111B: Steel pipe and tube; PCU331111331111D: Cold rolled steel sheet and strip and PCU331111331111F: Cold finished steel bars.

$$r_{it} - \tilde{p}_{it} = \beta_l l_{it} + \beta_k k_{it} + \beta_m m_{it} + \omega_{it} + \epsilon_{it}, \tag{C.6}$$

where $\tilde{p}_{it} \equiv \sum_j s_{ijt} P_{jt}$ is the plant-level output price deflator, and we use that the (log) input bundle can be decomposed into labor and capital input, scaled by their corresponding output elasticity β. The additional error term ϵ_{it} captures measurement error in either revenue or prices, as well as unanticipated shocks to output.

In order to take equation (C.6) to the data, we need to take a stand on the input allocation or what s_{ijt} is. We use revenue shares:

$$s_{ijt} = \frac{R_{ijt}}{\sum_j R_{ijt}}, \tag{C.7}$$

which we can directly compute in our data. The use of *revenue shares* restricts the markups to be the same across the products of a, potentially, multi-product plant. To see this it is useful to use the framework of De Loecker and Warzynski (2012) to recover markups and apply it to our setting. The markup μ_{ijt} is obtained using the FOC on input X of cost minimization:

$$\mu_{ijt} = \beta^X \frac{R_{ijt}}{P^X_{it} s_{ijt} X_{it}}. \tag{C.8}$$

Now, using equation (C.7), we get the following expression for markups:

$$\mu_{ijt} = \beta^X \frac{R_{it}}{P^X_{it} X_{it}} \tag{C.9}$$

which highlights that $\mu_{ijt} = \mu_{it}$ and $\forall j \in J_i$, with J_i the set of products produced by i.

Note that the reason we need to restrict markups across products within a plant to be constant, is because we see aggregate input use only at the plant level.[64] Finally, although we directly observe revenues for all product-plant combinations, we only observe product specific prices and assume away the variation across plants for a given product. In our empirical analysis, we rely on both the aggregate price index and our constructed plant-specific price index.

C.2 Input price deflator

The construction of the input price deflator is very similar to that of the output price deflator. There are, however, a few important differences. First, we need to distinguish between our three main input categories: labor, intermediate inputs and capital. Second, for some of the inputs, we observe plant-level input prices, that we can directly use to construct the deflator.

C.2.1 Labor and capital

We directly observe hours worked at the plant-level. We rely on the NBER capital deflator to correct the capital stock series. The use of an aggregate deflator implies that we assume a common user cost of capital across plants.

[64] See De Loecker and Warzynski (2012) and De Loecker et al. (2012) for a detailed discussion of the input allocation across products.

C.2.2 Intermediate inputs

The data on intermediate input use is potentially the most contaminated by input price variation, both in the cross-section and in the time series and, in particular, across the two types: VI and MM. As discussed in the main text, both technologies use vastly different intermediate inputs or use inputs at very different intensities. Note that the share of all intermediate inputs is not significantly different across types, but this masks the underlying heterogeneity. Due to the very different input use, we are concerned that the aggregate deflator does not fully capture the input price differences across plants and time.

We construct a plant-level intermediate input price deflator in the following way. We consider n intermediate inputs where n={Fuel (F), Electricity (E), Coal for coke (C), iron ore (I), iron and scrap (S), Others (O)}. In the data we observe expenditures by intermediate input (M^E_{int}) and prices for each input n (P^n_{it}).

The plant-level intermediate input price deflator is constructed as follows:

$$P^M_{it} = \sum_n s^n_{it} P^n_t \tag{C.10}$$

$$s^n_{it} = \frac{M^E_{int}}{\sum_n M^E_{it}} \tag{C.11}$$

$$P^n_t = N^{-1} \sum_i P^n_{it}. \tag{C.12}$$

In words, we compute the average price for a given input n, P^n_t, and weigh this by the plant's input share s^n_{it}. This structure still assumes a common input price for all plants for a given input n, but it recognizes that the intensity can vary across plants. In practice we compute (C.12) for all but the Fuel and Others categories. For those two, we directly rely on the NBER Fuel Price Deflator and the aggregate input price deflator, respectively. The other categories are a combination of various inputs for which we do not observe reliable input price data and, therefore, we decided to rely on the aggregate input price deflator. In terms of the log specification of the production function $m_{it} = \ln\left(\sum_n \frac{M^E_{int}}{P^M_{it}}\right)$.

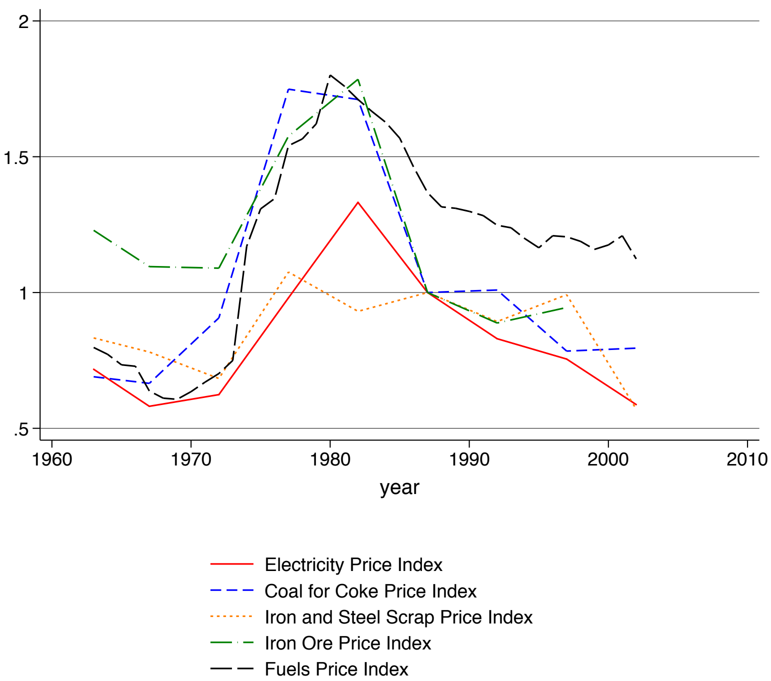
Table C.1: Intermediate Input use across Technology

Intermediate Input	Minimill	Integrated
Electricity (γ_E)	0.09	0.08
Coal for Coke (γ_C)	0.00	0.22
Iron Ore (γ_I)	0.00	0.10
Iron and Scrap (γ_I)	0.25	0.07
Fuel (γ_F)	0.06	0.08
Others (γ_O)	0.60	0.50

Note: We report average expenditure by intermediate input over total intermediate input at the plant level. Averages are computed overall type-year observations. The *Others* category captures a long set of smaller inputs such as chemicals and other components. See C.3 for the exact list.

Figure C.1: Price Trends for Inputs

Panel A: Material Inputs



Note: Base Year 1987=100. Price Indexes deflated by GDP deflator to express these in constant dollars. Electricity, Coal, Iron and Steel Scrap, and Iron Ore price indexes are author calculations from Census data. Fuels Price index is from the NBER-CES database.

Panel B: Labor Inputs

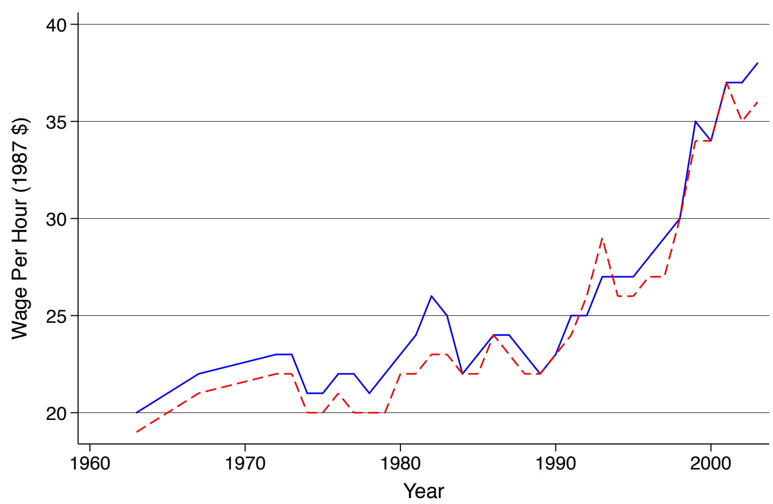


Table C.2: Input Shares: Materials

Panel A: Minimills Input Cost Share of Materials

Year	Scrap	Electricity	Fuels	Other
1963	.28	.07	.06	.60
1967	.26	.06	.05	.63
1972	.28	.08	.05	.59
1977	.30	.09	.07	.54
1982	.22	.13	.09	.55
1987	.30	.12	.05	.53
1992	.32	.10	.04	.53
1997	.37	.08	.04	.52
2002	.33	.09	.05	.52

Panel B: Vertically Integrated Input Cost Share of Materials

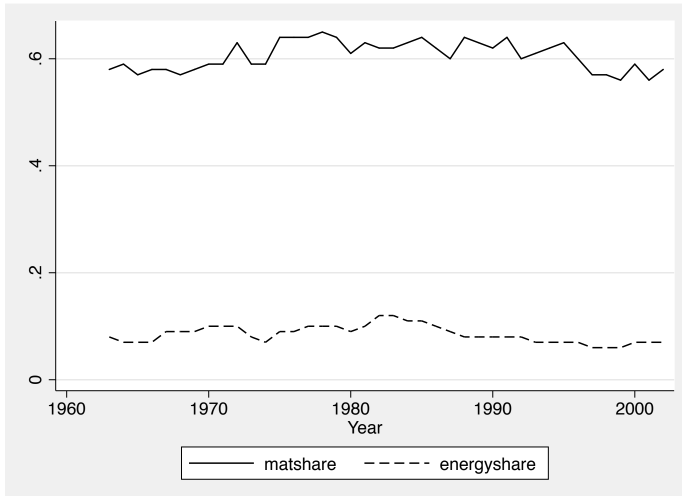
Year	Coal for Coke	Scrap	Iron Ore	Electricity	Fuels	Other
1963	.10	.08	.19	.02	.08	.52
1967	.10	.05	.16	.02	.06	.60
1972	.12	.05	.16	.03	.07	.57
1977	.17	.06	.13	.04	.14	.47
1982	.14	.07	.13	.06	.14	.46
1987	.12	.12	.12	.06	.08	.50
1992	.11	.08	.18	.06	.09	.47
1997	.09	.09	.19	.05	.09	.49
2002	.08	.11	.15	.06	.10	.50

Table C.3: Detailed Material Use (in 2002) in millions of dollars

	Minimills		Vertically Integrated	
	Value	Plants	Value	Plants
All other non-ferrous shapes and forms	168	(29)		
All other steel shapes and forms	1,182	(32)		
Cost of all other materials and components, parts, containers, and supplies consumed	1,962	(80)	3,058	(42)
Coal used in the production of coke			1,056	(24)
Carbon and graphite electrodes	206	(60)	46	(18)
Clay Refractories	98	(35)		
Dead-burned dolomite	26	(38)	61	(17)
Ferrochromium	32	(43)	67	(17)
Fluorspar	5	(29)		
Ferrosilicon	37	(59)	51	(23)
Ferromanganese, silicomanganese, manganese	182	(57)	125	(21)
Ferrovanadium	31	(53)		
Industrial chemicals	25	(26)	60	(18)
Industrial dies, molds, jigs, and fixtures	75	(28)		
Iron and steel scrap	3,697	(62)	1,398	(26)
Lime fluxes, including quicklime	95	(55)	150	(21)
Lubricating oils and greases and other petroleum products	26	(46)	94	(28)
Nickel	57	(34)	81	(16)
Nonclay refractories	107	(35)		
Other ferroalloys	75	(48)	191	(21)
Other fluxes	39	(41)		
Other	265	(165)	270	(72)
Oxygen	66	(51)	275	(24)
Total	8,703		6,983	

Note: Plants are the number of plants that report use of particular material. Products with fewer that 15 plants (either minimills or vertical led integrated integrated) that use the particular product are dropped due to disclosure restrictions.

Figure C.2: Trajectory of Energy and Intermediate Input Share in Output



Note: We compute the share of energy (intermediate inputs) using the deflated expenditure on energy and intermediate inputs, where the deflators are input specific, as a share of deflated total shipments. The data source is the NBER Manufacturing Database for industry code 3311.

D Production function and markups: theory and estimation

D.1 Including labor as a state

Our empirical framework can allow for adjustment costs in labor and therefore formally treating labor as state variable. We modify their approach and include both labor l_{it} and the technology indicator, ψ_i, as a state variable in firm's underlying dynamic problem. The firm's state is $s_{it} \equiv \{k_{it}, l_{it}, \omega_{it}, \psi_i\}$, and it's investment policy function is therefore given by:

$$i_{it} = i_t(k_{it}, l_{it}, \omega_{it}, \psi_i). \tag{D.1}$$

Following Olley and Pakes (1996) we invert the investment function to obtain a control function for productivity: $\omega_{it} = h_{\psi,t}(k_{it}, l_{it}, i_{it})$.[65] The first stage is in fact identical to the case in the main text:

$$\tilde{q}_{it} = \phi_{\psi,t}(l_{it}, m_{it}, k_{it}, i_{it}) + \epsilon_{it}. \tag{D.2}$$

This first stage serves to purge measurement error and unanticipated shocks to production form the variation in output ($\tilde{q}_{it}$). Consequently, after this first stage we know productivity up to the vector of (unknown) production function coefficients $\boldsymbol{\beta}$: $\omega_{it}(\boldsymbol{\beta}) \equiv \hat{\phi}_{it} - \beta_l l_{it} - \beta_m m_{it} - \beta_k k_{it}$.

A key component in the estimation routine is the law of motion on productivity that describes how a plant's productivity changes over time. The preliminary analysis indicated that exit, primarily by integrated mills, was substantial. We allow plant survival to depend on the plant's state variables; which

[65]We include labor as well and in fact including labor as another state is treated explicitly in Ackerberg et al. (2007) on page section 2.4.1 pp. 4222-4223. However, formally this requires revisiting the invertibility of the new investment policy function.

in our case includes the technology dummy in addition to productivity, capital and labor. Following Olley and Pakes (1996) we rely on a nonparametric estimate of plant's survival at time t, given the information set at time $t-1$, $\mathcal{I}_{t-1}$.

Define an indicator function χ_{it} to be equal to *1* if the firm remains active and *0* otherwise, and let $\underline{\omega}_{it}$ be the productivity threshold a firm has to clear in order to survive in the market place.

The selection rule can be rewritten as:

$$\begin{aligned} \Pr(\chi_{it}=1) &= \Pr\left[\omega_{it} \geq \underline{\omega}_t(l_{it}, k_{it}, \psi_i) | \mathcal{I}_{it-1}\right] \\ &= \Pr\left[\omega_{it} \geq \underline{\omega}_t(l_{it}, k_{it}, \psi_i) | \underline{\omega}_t(l_{it}, k_{it}, \mathbf{z}_{it}), \omega_{it-1}\right] \\ &= \rho_{t-1}(\underline{\omega}_t(l_{it}, k_{it}, \psi_i), \omega_{it-1}) \\ &= \rho_{t-1}(l_{it-1}, k_{it-1}, i_{it-1}, \psi_i, \omega_{it-1}) \\ &= \rho_{t-1}(l_{it-1}, k_{it-1}, i_{it-1}, i^L_{it-1}, \psi_i) \equiv \mathcal{P}_{it} \end{aligned}$$

From step 3 to 4 we use the fact that capital and labor are deterministic functions of $(k_{t-1}, l_{t-1}, \psi_i, i_{t-1}, i^L_{t-1})$. We use the fact that the threshold at t is predicted using the firm's state variables at $t-1$. As in Olley and Pakes (1996), we have two different indexes of firm heterogeneity, the productivity and the productivity cutoff point. Note that $\mathcal{P}_{it} = \rho_{t-1}(\omega_{it-1}, \underline{\omega}_{it})$ and therefore $\underline{\omega}_{it} = \rho^{-1}_{t-1}(\omega_{it-1}, \mathcal{P}_{it})$.

We consider the following productivity process:

$$\begin{aligned} \omega_{it} &= g_\psi(\omega_{it-1}, \underline{\omega}_{it}) + \xi_{it} \\ &= g_\psi(\omega_{it-1}, \rho^{-1}_{t-1}(\omega_{it-1}, \mathcal{P}_{it})) + \xi_{it} \\ &= g_\psi(\omega_{it-1}, \mathcal{P}_{it}) + \xi_{it}, \end{aligned} \tag{D.3}$$

We recover estimates of the production function coefficients, $\boldsymbol{\beta}$, by forming moments on this productivity shock ξ_{it}. The identification of these coefficients relies on the rate at which inputs adjust to these shocks. In particular, we allow both labor and capital to be dynamically chosen inputs, whereby current values of capital and labor do not react to current shocks to productivity (ξ_{it}). Plants do, however, adjust their intermediate input use (scrap, energy, other material inputs) to the arrival of a productivity shock ξ_{it}. While allowing for adjustment costs in capital is fairly standard in this literature, we also allow for adjustment costs in labor. One could motivate this by appealing to for example the relatively high unionization rates in the U.S. steel industry raise the potential for adjustment frictions for labor.

We rely on the following moments:

$$E\left(\xi_{it}(\boldsymbol{\beta})\begin{bmatrix} l_{it} \\ m_{it-1} \\ k_{it} \end{bmatrix}\right) = 0. \tag{D.4}$$

The production function coefficients are very similar and in particular the coefficient on labor barely changes. So both the production function coefficients and the associated reallocation analysis leed to the same results, both in terms of point estimates and in terms of statistical significance.

D.2 Recovering markups

We briefly discuss how we recover markups using our plant-level panel on production and prices. Our approach to recovering markups follows De Loecker and Warzynski (2012). In the rest of this section, we briefly review the approach. In addition to the production function we introduced before, we only have to assume that producers active in the market minimize costs. Let $\mathbf{V}_{it}$ denote the vector of variable inputs used by the firm. We use the vector $\mathbf{K}_{it}$ to denote dynamic inputs of production. Any input that faces adjustment costs will fall into this category; capital is an obvious one, but our framework allows us to also include labor.

The associated Lagrangian function is:

$$\mathcal{L}(V_{it}^1, ..., V_{it}^V, \mathbf{K}_{it}, \lambda_{it}) = \sum_{v=1}^{V} P_{it}^{v} V_{it}^{v} + \mathbf{r}_{it}\mathbf{K}_{it} + \lambda_{it}(Q_{it} - Q_{it}(V_{it}^1, ..., V_{it}^V, \mathbf{K}_{it}, \omega_{it})) \tag{D.5}$$

where P_{it}^{v} and $\mathbf{r}_{it}$ denote a firm's input prices for a variable input v and dynamic inputs, respectively. The first-order condition for any variable input free of adjustment costs is

$$\frac{\partial \mathcal{L}_{ft}}{\partial V_{it}^{v}} = P_{it}^{v} - \lambda_{it} \frac{\partial Q_{it}(.)}{\partial V_{it}^{v}} = 0. \tag{D.6}$$

where the marginal cost of production at a given level of output is λ_{it}, as $\frac{\partial \mathcal{L}_{it}}{\partial Q_{it}} = \lambda_{it}$. Rearranging terms and multiplying both sides by $\frac{V_{it}}{Q_{it}}$, generates the following expression.

$$\frac{\partial Q_{it}(.)}{\partial V_{it}^{v}} \frac{V_{it}^{v}}{Q_{it}} = \frac{1}{\lambda_{it}} \frac{P_{it}^{v} V_{it}^{v}}{Q_{it}} \tag{D.7}$$

Cost minimization implies that optimal input demand is realized when a firm equalizes the output elasticity of any variable input V_{it}^{v} to $\frac{1}{\lambda_{it}} \frac{P_{it}^{v} V_{it}}{Q_{it}}$.

Define markup μ_{it} as $\mu_{it} \equiv \frac{P_{it}}{\lambda_{it}}$. As De Loecker and Warzynski (2012) show, the cost-minimization condition can be rearranged to write markup as:

$$\mu_{it} = \theta_{it}^{v} (\alpha_{it}^{v})^{-1}. \tag{D.8}$$

where θ_{it}^{v} denotes the output elasticity on an input V^{v} and α_{it}^{v} is the revenue share of variable input v, defined by $\frac{P_{it}^{v} V_{it}^{v}}{P_{it} Q_{it}}$, which is data. This expression will form the basis for our approach: We obtain the output elasticity from the estimation of a production function and only need to measure the share of an input's expenditure in total sales. In particular, in our setting, $\theta_{it}^{v} = \beta_{m}$.

In our context, the output elasticities are obtained by relying on product-specific price deflators, and potentially leave plant-level price variation left uncontrolled for. The latter is expected to bias the output elasticity downward and, therefore, downward-bias the level of the markup. Under a Cobb-Douglas production technology, this has no implications for the time-series pattern of markups and on the comparison of markups across minimills and integrated producers – as long as the output elasticity is fixed across types, which we explicitly allowed for and we could not find any statistical significant difference between types.

D.3 Technology-specific production functions

In the main text we start allowing for technology-specific production functions, but we cannot reject the null hypothesis (for individual and the sum of the coefficients) at any reasonable level of significance level, that the technologies have different (Cobb-Douglas) coefficients. Consequently we proceed our main analysis with a set of common production function coefficients.

In this Appendix we that even in that setting our model actually allows for a fixed proportion production function for the bundle of intermediates (and we could in principal allow the same for labor although that a look at the data does not seem to suggest any meaningful differences), and at the same time allows us to compare the efficiency of plants of different technologies. We turn to both the data restrictions, and the underlying theoretical framework we rely on. The theoretical framework was in fact determined by analyzing the more disaggregated intermediate input data.

D.3.1 Conceptual framework

Regardless of the differences, in any input of production, at *a lower level of aggregation*, our approach rests on the following production fuction:

$$Q = L^{\beta_l} K^{\beta_k} M(\psi)^{\beta_m} \Omega \tag{D.9}$$

where $M(\psi)$ is our aggregate bundle of intermediate inputs which is very different across types. Given the specifics of both technologies in this industry we let this aggregate bundle be given by[66]:

$$M(\psi) = \min\{\gamma_F^{\psi} F, \gamma_E^{\psi} E, \gamma_C^{\psi} C, \gamma_I^{\psi} I, \gamma_S^{\psi} S, \gamma_O^{\psi} O\} \tag{D.10}$$

It is irrelevant whether we think of this production taking place inside the same plant or whether the plant can buy this aggregate intermediate input $M(\psi)$ from a competitive supply at price P^M (just as in our Appendix on the Input price index). Ultimately what we use data on is the deflated expenditure on total intermediates (our $\tilde{m}$ input variable). This observation is important as it allows us to rely on labor, capital and total intermediate inputs and go ahead and estimate the production function over these three well defined variables, and makes the comparison to the literature straight forward.

Of course with ideal data on all M_n inputs, we could in turn analyze that production process. Note that this would not benefit our analysis whatsoever: we are interested in the productivity at the plant level and how it differs across plants and time. The production process one level below would not have any implications for this analysis. We just find it worthwhile reporting that both technologies get very similar shares on this total intermediate input bundle, about sixty eight, but this is nothing deep. The more disaggregated intermediate input use is of course as expected very different across technologies.

An additional benefit, at least to us, is that modeling the more disaggregated intermediate inputs in this way is that changes to individual intermediate input's prices do not directly affect the demand for the other intermediate inputs since they have to move in exact proportions. However, the total input price for the intermediate input bundle will change, as reflected by the weight of the intermediate input, and will have an effect on the total intermediate input use.

D.3.2 Disaggregation

Having said this, there are of course substantial differences between Minimills and Integrated plants in terms of their input use. If we were to estimate production functions at such a level we would most likely find different production function coefficients. However, the data is not good enough for us to estimate a disaggregated-material production function, or the disaggregation does not seem to suggest much variation across types anyway (which is the case for the labor input).

[66]This is precisely in line with the referee's comment on using more institutional details and knowledge in the modeling of the production function, given that we are only concerned with estimating the production function for one particular industry.

For labor use at the plant-level, it turns out that salaries per worker at minimills and vertically integrated plants are very similar, and move in the same direction over time, as can be seen in Figure C.1 Panel B. Likewise, the skill mix of workers, say blue versus white collar, does not seem to be very different between minimills and vertically integrated plants.

For materials, there is more scope for variation in input use, and differences between minimills and vertically integrated plants. Table C.1 reports the average share of an intermediate input's expenditure in total intermediate input expenditure by plant. Given our specification for the intermediate input bundle $M(\psi)$, these correspond to the parameters ($\boldsymbol{\gamma}$).

The results are as expected: minimills do not use any coal and iron ore, while integrated plants use much less scrap. It is interesting to note that both technologies are quite similar in electricity and fuel consumption. While this table shows the average over our sample period, Tables C.2 further shows that these shares are extremely stable over time. We see this again as an important piece of data to support our interpretation of the productivity differences as coming from the overall (Hicks-neutral) efficiency differences.

More specific to the issue of *data quality* at the lowest level of aggregation for intermediate inputs. Table C.3 breaks out material use by plant for 2002. You can see that even for items that *all* Minimills should use, such as Iron and Steel Scrap, a large fraction of plants do not report using any of it. Likewise, some materials that *all* Vertically Integrated plants should use, such as Coal Used for Coke, we see a large number of plants that report having a blast furnace also reporting using no Coal for Coke. We should emphasize that all of these inputs are necessary for a vertically integrated plant. So there is a substantial amount of non-response in the material trailer that prevents us from using most plants to estimates a disaggregated production function. Disregarding the issues of selection that would show up if we dropped plants that did not report using a complete list of materials, we are close enough to the disclosure threshold at Census to make any reduction in the sample a serious impediment.[67]

E Deriving decompositions

We provide more details on how we derive the various decompositions introduced in the main text. We start with the standard aggregate productivity definition:

$$\Omega_t = \sum_i s_{it}\omega_{it} \tag{E.1}$$

where we define:

$$s_{it} = \frac{R_{it}}{\sum_i R_{it}} \tag{E.2}$$

$$R_t = \sum_i R_{it} \tag{E.3}$$

and R_{it} is plant-level total sales.

[67] This type of missing data is pervasive in the Census. In fact, the Steel Industry is perhaps the industry where collection of these items is liable to be the most precise, and the Census of Manufacturing is also one of the better plant level datasets. So even in the "best-case" conditions, we cannot do a disaggregated materials production function analysis.

E.1 Standard OP

Olley and Pakes show that (E.1) can be written as:

$$\begin{aligned}\Omega_{it} &= \bar{\omega}_t + \sum_i (s_{it} - \bar{s}_t)(\omega_{it} - \bar{\omega}_t) \\ &= \bar{\omega}_t + \Gamma_t^{OP}\end{aligned} \tag{E.4}$$

with N_t the number of active plants at time t and:

$$\bar{\omega}_t = N^{-1} \sum_i \omega_{it} \tag{E.5}$$

$$\bar{s}_t = N^{-1} \sum_i s_{it} \tag{E.6}$$

E.2 Deriving the Between covariance

We show that aggregate productivity can be decomposed in a between technology covariance component and an average type-specific productivity component, which in itself is decomposed into type-specific within and covariance terms.

Start from (E.1) and simply break up the sum into the two technology types, i.e. $\psi = \{MM, VI\}$:

$$\begin{aligned}\Omega_t &= \sum_{i \in \psi = MM} s_{it}\omega_{it} + \sum_{i \in \psi = VI} s_{it}\omega_{it} \\ &= s_t(\psi = MM) \sum_{i \in \psi = MM} \frac{s_{it}}{s_t(\psi = MM)} \omega_{it} \\ &+ s_t(\psi = VI) \sum_{i \in \psi = VI} \frac{s_{it}}{s_t(\psi = VI)} \omega_{it}\end{aligned} \tag{E.7}$$

The second line multiplies and divides each term by the relevant total market share of the type in the industry, i.e. $s_t(\psi) = \sum_{i \in \psi} s_{it}$.[68]

The last equation can now be rewritten as another weighted sum where we now sum over two groups: minimills and integrated producers:

$$\Omega_t = \sum_{\psi} s_t(\psi)\Omega_t(\psi) \tag{E.8}$$

where

$$\Omega_t(\psi) = \sum_{i \in \psi} \frac{s_{it}}{s_t(\psi)} \omega_{it} = \sum_{i \in \psi)} s_{it}(\psi)\omega_{it} \tag{E.9}$$

[68] The OP-decomposition relies crucially on the property that the market shares sum to one. However, if we were to simply split the summation across the two types, we could not isolate the within covariance term. To see this, note that $\sum_{\psi} \Omega_t(\psi) \neq \Omega_t$, due to the fact that $\sum_{\psi,i} s_{it}(\psi) > 1$.

The second line uses that the market share of a plant in the total industry divided by the total type-specific market share is equal to the plant's market share in the type's total sales ($s_{it}(\psi)$). Formally:

$$s_{it}(\psi) = \frac{s_{it}}{s_t(\psi)} \tag{E.10}$$

After having transformed the aggregate productivity expression into (E.8), we can rely on the same insight as OP and decompose aggregate productivity into a unweighted average and a covariance component. By transforming the expression using type-specific market shares we guarantee that the plant market shares sum to one; a necessary condition for the OP decomposition.

Applying the OP decomposition idea to (E.8) gives us:

$$\begin{aligned} \Omega_t &= \bar{\Omega}_t(\psi) + \sum_{\psi} (s_t(\psi) - 0.5)(\Omega_t(\psi) - \bar{\Omega}_t(\psi)) \\ &= \bar{\Omega}_t(\psi) + \Gamma_t^B \end{aligned} \tag{E.11}$$

E.3 Within type decompositions

Starting from equation (E.11) we simply apply the OP decomposition by type ψ and use the fact that we only have two technology types to obtain an expression for the average component:

$$\begin{aligned} \bar{\Omega}_t(\psi) &= \frac{1}{2} \sum_{\psi} (\Omega_t(\psi)) \\ &= \frac{1}{2} \sum_{\psi} (\bar{\omega}_t(\psi) + \sum_{i \in \psi} (s_{it}(\psi) - \bar{s}_t(\psi))(\omega_{it} - \bar{\omega}_t(\psi))) \\ &= \frac{1}{2} \sum_{\psi} (\bar{\omega}_t(\psi) + \Gamma_t^{OP}(\psi)) \end{aligned} \tag{E.12}$$

where we denote the average market share across a given type by $\bar{s}_t(\psi) = N_{\psi}^{-1} \sum_{i \in \psi} s_{it}(\psi)$.

E.4 Total decomposition

To arrive at the expressions used in the main text we introduce $\Gamma_t(\psi)$ to denote a covariance of a given type and use superscripts B and OP to indicate whether the covariance is between or within the type, respectively. This gives us the following total decomposition of aggregate productivity:

$$\Omega_t = \frac{1}{2} \sum_{\psi} [\bar{\omega}_t(\psi) + \Gamma_t^{OP}(\psi)] + \Gamma_t^B(\psi) \tag{E.13}$$

If there was no entry or exit we can then directly evaluate the share of each component by tracking Ω_t over time. We incorporate the turnover process by relying on dynamic decompositions within a given type and can always scale the various subcomponents back to the decomposition discussed above.

F Product reallocation

We do not see any evidence for reallocation of products *within* vertically integrated plants in response to the entry of minimills. It seems like this type of intensive margin, within plant product switching, is not an important factor in the industry, most likely due to the high costs of changing the production process.

Table F.1 shows, for vertically integrated plants, the standard deviation, both within plant and between plants, for the fraction of revenues accounted for by sheet products: the sheet specialization ratio. This ratio is given by the share of revenues accounted for by hot and cold rolled sheet. Notice that the standard deviation if all plants were fully specialized into sheet or into bar would be given by the usual binomial formula: $\sqrt{p(1-p)} = 0.47$. So a standard deviation of 0.40 indicates that plants are reasonably close to being fully specialized in bar or sheet, and the standard deviation within a plant of their sheet specialization ratio is only 0.11. This indicates that most of the movement in production of sheet is happening between plants, not within the plant.

As well, we do not see a large change in the sheet specialization ratio for plants that produce some sheet products over time. Thus, most of the reallocation towards sheet production is happening at the extensive margin of plant selection. Note that it is precisely because of the lack of product reallocation within plants, that we find such an important role for the head-to-head competition in the bar market. VI plants did not reallocate away from the bar products, and instead we saw an exit of most bar-producing integrated mills, leaving the high productivity sheet producing alive. Of course, this begs the question of *why* the integrated mills could not switch production towards the high quality steel products (like sheet). A simple model-based answer would be to think of each product to have a productivity threshold associated to it ($\overline{\omega}_j$), which a plant has to clear in order to be able to produce product j. In this context it seems plausible that sheet and bar products are ranked as follows: $\overline{\omega}$(sheet)$>$ $\overline{\omega}$(bar). As competition for bar products increased, due to the minimill entry, the integrated mills who focussed primarily on bar products, were simply not productive enough to engage in higher quality steel.

Table F.1: Product Mix: Within and Between Plants

Sheet Specialization Ratio	
Mean	0.36
Standard Deviation	0.40
Between Std.	0.38
Within Std.	0.11
Observations	657
Plants	124