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

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First version February 2012, Current version November 26, 2012

Abstract

This paper studies the role of technology and competition in industry-wide productivity growth. We rely on a unique producer-level dataset covering U.S. steel producers between 1963 and 2002 to measure the impact of a drastic new production technology, the minimill, on aggregate productivity. We find that minimills were on average 11% more productive than the old vertically integrated technology. Moving output from vertically integrated producers to minimills accounts for 27% of the productivity gains in this industry. While the new technology started out with a significant productivity premium, by 2002 minimills and vertically integrated producers have similar efficiency. However, virtually all of the catch-up is due to the exit of vertically integrated producers of bar products who competed in the same product segments as minimills. This additional selection and reallocation effect accounts for a further 40% of productivity gains over the period.

Keywords: Productivity; Technology; Competition.

*This project was funded by the Center for Economic Policy Studies (CEPS) at Princeton University and the Center for Global Economy and Business (CGEB) at New York University. 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 Rob Clark, Liran Einav, Ariel Pakes, Kathryn Shaw, Chad Syverson, Raluca Dragusanu, and seminar participants at the HEC Montreal, Economic Analysis Group at the Department of Justice, CUNY Graduate Center, NBER, NYU Stern, NYU IO Day, and Stanford University for helpful conversations. This paper uses restricted data that was 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.

1 Introduction

A large literature has emphasized the role of the reallocation of resources across producers in aggregate productivity growth. Indeed, industry productivity rises not only because the average plant becomes more productive, but due to shifts in inputs from less to more productive plants.

Although by now it is well established, both at 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.[1] In this paper we focus on two distinct potential drivers of reallocation, technology and competition, which we directly observe in our data, and we verify to what extent they contributed to productivity growth.

Some prominent studies on the triggers of productivity growth are the work of 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. As well, the work of Hortaçsu and Syverson (2004), Bloom, Eifert, Mahajan, McKenzie, and Roberts (2011), and Jarmin, Klimek, and Miranda (2009) shows that factors such as vertical integration, management, and large retail chains lead to systematic differences in productivity between plants.

To make progress we focus on one particular industry, the U.S. steel sector, for which we observe detailed producer-level production and price data. Our setting is well suited to directly measure the separate role of *technological change* and *competition* in productivity growth. We identify the impact of technology through the introduction of a new production process for steel products, i.e. the entry of minimills, whereas the change in competition is identified through changes in prices and markups and increased import competition. The fact that we observe plant-level data for a forty year period, 1963-2002, allows us to study the long run implications of both technology and competition.

The U.S. steel industry shed about 75 percent of its workforce between 1962 to 2005, or about 400,000 employees. This dramatic fall in employment has far reaching economic and social implications. For example, between 1950 to 2000, Pittsburg dropped from the 10th largest city in the United States to the 52nd largest. The

[1] For instance Melitz (2003) shows how trade liberalization impacts aggregate productivity through a reallocation towards more productive firms, while Foster, Haltiwanger, and Krizan (2001) and Bartelsman, Haltiwanger, and Scarpetta (2009) document the role of reallocation empirically using firm-level data.

main reason for this shrinking population is that Pittsburg used to be the center of the U.S. Steel Industry.

While employment in the Steel Sector fell by a factor of five, shipments of steel products in 2005 reached the same level of the early sixties.[2] Thus output per worker has grown by a factor of five, and total factor productivity (TFP) has increased by 38 percent. Over the last three decades, this makes the steel sector one the fastest growing industries among large manufacturing industries, 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 the change in output, employment and TFP over the period 1972-2002 for the U.S. steel sector and compare it to the mean and median manufacturing sector's experience.[3]

Table 1 points out the unique feature of the steel industry: the period of impressive productivity growth, 28 percent compared to the median of 3 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 5 percent for the average sector.[4]

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

We find that the main reason for the rapid productivity growth and the associated decline in employment is not a steady drop in steel consumption, nor a consequence of globalization, and not even 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 industry total factor productivity (henceforth TFP). In addition, minimills' productivity steadily increased through a slow process of learning by doing. Therefore we can directly attribute almost half of the aggregate productivity growth to the mere entry of the new technology.

[2]Numbers are based on the NBER manufacturing database.

[3]We only consider large industries with more than 10 billion dollars in sales in 2002.

[4]This table masks the distinct periods of demand decline and demand recovery in our sample period by reporting the change in output and employment over the entire sample period. We revisit this in great detail in section 3.

However, the older technology was not entirely displaced. Instead vertically integrated producers experienced a dramatic resurgence of productivity, and by 2002 are as productive as minimills. This resurgence was not driven by improvements at integrated plants. Instead, less productive vertically integrated plants were driven out of the industry, and output was reallocated to more efficient producers.

The remainder of the paper is organized as follows. In the next section, we discuss the rich plant-level data from the Census. In section 3 we present five key facts which help guide the empirical analysis which we take up in section 4. We discuss alternative explanations in section 5 and conclude in the last section.

2 Data

We study the production of steel: plants engaged in the production of either carbon or alloy steels.[5] 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 covering the period 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 (henceforth CMF), the Annual Survey of Manufacturers (henceforth ASM), and the Longitudinal Business Database (henceforth 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.[6] The CMF is sent to all steel mills every five years, while the ASM is sent to about 50% of plants in non-Census years. However, all plants with over 250 employees are sampled by the ASM, and as such the ASM encompasses over 90% of the output of the steel sector.

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

We rely on our detailed micro data to break up steel mills into two technologies: Minimills (MM, hereafter) and Vertical Integrated (VI, hereafter) Producers. VI production takes place in two steps. The first stage takes place in a blast furnace,

[5] Throughout our analysis we consider 9 different product segments and we introduce the different products in section 2.2.

[6] Plants occasionally switch in and out of the steel mill sector. In the data appendix, we discuss how to sort out plants that switch sectors, based on how often these plants are coded as steel mills.

which combines coke, iron ore, and limestone to produce pig iron and slag. The pig iron, along with oxygen and fuel, is then used in a basic oxygen furnace (henceforth BOF) to produce steel.[7] 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.[8]

In contrast, MM's are primarily identified by the use of an electric arc furnace (henceforth EAF) to melt down a combination of scrap steel and direct reduced iron. These mills have a far smaller efficient scale, and thus are on average an order of magnitude smaller than vertically integrated producers. Historically EAFs were used to produce lower quality steels, such as those 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 have enabled them to produce certain types of steel sheet products as well.[9]

We classify plants into minimills, vertically integrated plants, and rolling mills using their response to a specific questionnaire on steel mills attached to the 1997, 2002, and 2007 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 the Data Appendix. Table 2 shows summary statistics for the sample of MM and VI plants. The average VI plant had shipments of 647 million dollars, of which 47% is value added, while the average MM plant shipped 153 million dollars, of which 44% is value added.

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.

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

[8] For references on the differences between minimills and vertically integrated plants and the production process for steel, see Fruehan (1998) p.1-12, Crandall (1981) p.5-15.

[9] EAF's have a long history in steel making. However, before the 1960s they were primarily used to produce specialty steels.

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 seventies. A decade later only 40 billion dollars were shipped; or put differently the sector's shipments decreased by more than half.[10]

Total employment on the other hand consistently decreased even during the recovery of output in the late eighties and throughout the nineties. The employment panel of Figure 1 shows that total employment fell from 500,000 to 100,000 employees. This is one of the sharpest drops in employment experienced by any sector of the U.S. economy. By the year 2000, the steel industry employs a fifth of the workers 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.[11] Total material use tracks output quite closely, while labor and capital fall continuously over the entire period; which suggests that TFP had to increase to offset the sharp drop in labor and capital.[12]

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 in which we regress direct measurable characteristics on a dummy variable indicating whether a plant is a vertical integrated producer. We consider a log specification such that the coefficient on the technology dummy directly measures the percentage premium of VI plants in terms of the relevant characteristic. Table

[10]Shipments are deflated using 1987 USD and the producer price index for steel produced by the Bureau of Labor Statistics PCU331111331111. This change in shipments captures both changes in prices and output, and we decompose both components in detail later on. Appendix **??** discusses deflators in more detail.

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

[12]Table 15 in Appendix B lists the growth in output and the various inputs for a five year period. For this aggregate analysis we rely on the NBER's five factor TFP estimate. See Bartelsman, Becker, and Gray (2000) for more detail.

3 lists the set of estimated coefficients.

These regressions confirm that vertical 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 MM. 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. In order to compare TFP across both types we need to estimate the production functions. We turn to this in section 4.

In addition to the average premium over the entire sample, we report the time specific coefficients. Across all the various characteristics the VI coefficient falls over time. Most notably, shipments per worker are about 23 percent higher for VI plants in 1963, but by 2002, there is 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 retain a larger scale.

The coefficients on the wage of 6%, shown in the last row of Table 3, 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.[13] It is interesting to note that the wage gap between both technologies closes over time.

An important difference between MM and VI producers is the set of products they manufacture. Figure 2 shows, in 1997 MM's accounted for 59% and 68% of shipments of steel ingots and hot-rolled bar, but only 15% and 14% of hot and cold rolled sheet. MM 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 MM changes dramatically over the last 40 years. Figure 2 shows that in 1977 MM's produced 27% of steel ingots and 24% of hot-rolled bar. Between 1977 and 1982, MM's increased their share of these products to 40%, and by 2002 81% of hot-rolled bar is produced by MM's. In contrast, in 1997, only 15% and 14% of hot and cold rolled sheet are produced by MM's.[14] Thus the market share of MM in the *higher quality product*

[13] See Hoerr (1988) and in particular page 16 for evidence of the role of unionization on wages for VI and MM producers.

[14] Giarratani, Gruver, and Jackson (2007) discuss the entry of Minimills into the production of sheet products around 1990.

segments, sheet products, was rather stable up to 1997, after which their market shares did increase substantially.

3.3 A Stable Product Mix over Time

We now turn from the production side to changes in the product market for Steel. Table 4 shows the product mix of the steel industry.[15] It is worth mentioning that over forty years the product mix for steel has barely changed. Hot-rolled sheet accounts for 23% of shipments in 1963 and 31% in 2002, and hot-rolled bar accounts for 23% of shipments in 1963 and 22% 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 it's products.[16]

3.4 Heterogeneous Price Trends Across Products

While the product mix of steel producers has been relatively unchanged from 1963 to today, the prices for these products have dropped considerably, which is unsurprising given the large increases in TFP in the industry. 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% of shipments in 1997.[17]

Figure 3 shows that the prices of all steel products followed a very similar, and gradually increasing, pattern up to 1980. But from 1982 to 2000, there is a 50% drop in the real price of steel. This dramatic drop in prices tell us that while shipments of steel in dollars have dropped since 1980, shipments in *quantity* have gradually increased since the mid-eighties (see panel 1 of Figure 1).[18]

Second, 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 for hot and cold

[15] 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). More details on these product categories can be found in the data appendix.

[16] The one product whose shipments fall notably over this period are steel ingots and semi-finished shapes (henceforth SISS). However, SISS is primarily used in rolling mills to produce steel sheet. Since the mid 1990's with the development of slab casting technologies, steel is directly shaped into sheets at the mill.

[17] 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.

[18] External support to this claim can be found in the various annual reports of the American Iron and Steel Institute (American Iron and Steel Institute, 2010) where total ton of steel are recorded annually. In this data, quantity produced increased by about thirty percent between 1982 and 2002.

rolled sheet. Remembering that sheet steel is primarily produced by VI producers, it is interesting to note that prices for bar and ingot products fell by 10% more than those for sheet products in 1982-1984, precisely at the point MM were increasing their share of bar and ingot products. The price heterogeneity across products and time is substantial and therefore we need to control for price differences when estimating the production function in order to get reliable estimates of productivity, and consequently to correctly identify the productivity effect of the arrival of the minimills and their associated increased competition.[19]

3.5 Simultaneous Entry and Exit

From Figure 1, we know that the number of plants increased over time. In Table 5 we go a step further, and show both the number of MM and VI plants that entered or exited, and the market share represented by these plants. There is marked entry of new plants in the early eighties, a period where the entire industry as a whole was severely contracting. The market share of entrants from 1982 to 1992 is 20 percent, versus 5 percent in the previous two decades, while the market share of exitors is 18 percent during this period. However, most entry in this period is due to minimills, and most exit is from vertically integrated producers.[20] 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 discussed the difference in performance between MM and VI producers. This implies that there is a large potential role for reallocation across these technologies in explaining productivity growth. This paper is precisely concerned with studying the productivity differences in greater detail and verifying to what extent the entry of minimills contributed to the stark aggregate productivity growth in the industry.

First, we start out by presenting our empirical framework. Second, we rely on our productivity estimates to verify the importance of reallocation, both across and within technology, in productivity growth. We consider both static and dynamic

[19] See Klette and Griliches (1996) and De Loecker (2011) on the importance of correcting for unobserved price heterogeneity in the estimation of production functions.

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

decompositions, which enables us to investigate the importance of entry and exit in productivity growth. Finally, we relate a direct measure of competition, markups, to the reallocation analysis by connecting markups to the covariance of market share and productivity.

4.1 Productivity Differences Across Technology

Denote each technology – either MM or VI – as $\psi \in \{VI, MM\}$.[21] 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 guarantee that we recover productivity, ω_{it}, using plant/product revenue data we construct a plant-specific price (P_{it}) . We assume that each product j is homogeneous, and we directly observe each price P_{jt} in the product-level BLS price data. Furthermore we follow the literature and consider a Cobb-Douglas specification by type. We can therefore write equation (1) as:

$$R_{ijt} = L_{ijt}^{\alpha_l} M_{ijt}^{\alpha_m} K_{ijt}^{\alpha_k} \exp(\omega_{it}) P_{jt} \tag{2}$$

Since we are interested in recovering a measure of productivity at the plant level, we aggregate up to recover total plant-level sales. A common restriction in these type of data is that we do not directly observe the input use by product (see Foster, Haltiwanger and Syverson 2008). We allocate inputs across products using product

[21] Plants cannot *change* from one technology to another. In the steel industry, a plant never switches technology, such as becoming a minimill.

specific sales shares: $s_{ijt} \equiv \frac{R_{ijt}}{R_{it}}$.[22] After aggregating (3) to the plant level we obtain:

$$\frac{R_{it}}{\sum_j s_{ijt} P_{jt}} = L_{it}^{\alpha_l} M_{it}^{\alpha_m} K_{it}^{\alpha_k} \exp(\omega_{it}) \tag{3}$$

Although the focus in the literature has mostly been 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}, is potentially the most contaminated by input price variation, both in the the time series, and in the cross section, in particular between MM and VI plants. Both technologies use vastly different intermediate inputs, or use inputs at very different intensities, and we therefore expect the relevant input price to vary substantially across plants of different technologies.

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. The use of a common deflator implies that we assume a the same cost of capital across plants.

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 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 shares are the share of an intermediate n in total intermediate input use. Deflated intermediate input use is thus given by $M_{it} = \sum_n \frac{M_{int}}{P_{it}^M}$.

This leads to the following empirical specification for the production function we take to the data:

$$r_{it} = \beta_l l_{it} + \beta_k k_{it} + \beta_m m_{it} + \omega_{it} + \epsilon_{it} \tag{4}$$

where lower cases indicate logs of deflated variables when appropriate.[23] We allow for unanticipated shocks to production and measurement error in output and

[22] 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, and are mainly after recovering measures of plant-level productivity that are not contaminated by price variation across plants and time.

[23] E.g. $r_{it} = \ln\left(\frac{R_{it}}{\sum_j s_{ijt} P_{jt}}\right)$ and $m_{it} = \ln\left(\sum_n \frac{M_{int}}{P_{nt}}\right)$. With a slight abuse of notation we use $\tilde{x}$ to denote the undeflated version of a variable x.

prices, as captured by ϵ_{it}. In the next section we report the production function coefficients, and the corresponding minimill productivity premium, if any, under various specifications.

4.1.2 Production function coefficients and technology premium

We start by considering a few baseline specifications for the standard Cobb-Douglas production function. Table 6 presents estimates of the production function. Columns I, II and III show results with output defined as sales deflated by an aggregate price deflator, while Columns IV, V, and VI show estimates using output deflated by plant specific prices. Columns I, II, VI, and V report OLS estimates, while Columns III and VI (GMM) present investment control function estimates of productivity (Ackerberg, Benkard, Berry, and Pakes, 2007). We underscore that it is important in this context to explicitly allow the underlying demand and technology factors to vary with the technology type. More specifically, we index both the investment policy function, the exit rule and the productivity process with the technology type indicator. We refer Appendix E.1 for more details on this investment control function procedure.

The production function coefficients, across all specifications, are stable and have reasonable estimates of returns to scale and output elasticities. An important test for our purpose is to check whether minimills and vertical integrated producers rely on different input factor shares. In order to test this we simply interact every coefficient with our technology type dummy and run a F-test on the joint significance of the interacted coefficients. In doing so, we cannot reject that both technologies produce under the same output elasticities of labor, materials, and capital. Four main results emerge from this analysis.[24]

First, minimills are on average more productive as indicated by a negative coefficient on the VI dummy. Under specification I minimills have on average a 3 percent higher TFP than vertically integrated producers, yet this is not statistically significant. This result is surprising, both since minimills are thought to be more productive by participants in the industry, and these plants have a large increase in

[24] At first it might seem surprising that for instance 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. For instance, in 2002, Iron and Steel Scrap represents 42% of the coded material inputs for minimills, and Coal for the production of Coke represents 15% of the coded material inputs for vertically integrated plants.

market share over the sample period.

Second, the TFP premium for minimills decreases over time as indicated by the positive coefficient of 0.3% on the technology-year. Although this coefficient is relatively small in magnitude, one has to keep in mind that our sample is about 40 years, which implies that by the end of our sample the TFP premium for MMs has disappeared. This will be important when we compute our decompositions, i.e. we expect the impact of minimills in aggregate productivity growth to be concentrated at the beginning of the sample.

Third, the results in Panel B demonstrate the importance of controlling for unobserved prices in the revenue generating production function (Panel A) and confirms the findings of De Loecker (2011). In particular, when we correct for plant-specific prices we find that the minimill TFP premium is twice as high, and becomes significant. The impact of including detailed price data on the technology coefficient is as expected since we know from Figure 3 that VI plants are active in the relatively higher quality segments where producer prices are higher. Therefore when we do not properly deflate the sales data, the productivity premium for minimills is dampened.[25] This result is not surprising, and it is useful to write out the potential bias induced by not deflating either output or inputs in light of our productivity analysis. We refer the reader to De Loecker (2011) and De Loecker, Goldberg, Khandelwal, and Pavcnik (2012) for more details on the impact of unobserved output and input prices, respectively. Using our production function it is easy to show that without deflating the following equation is estimated on the data (in fact Panel A considers such as specification):

$$\tilde{r}_{it} = \beta_l l_{it} + \beta_k k_{it} + \beta_m \tilde{m}_{it} + \omega_{it} + p_{it} - \beta_m p_{it}^M + \epsilon_{it} \tag{5}$$

This equation relates plant-level revenue to (physical) labor, capital, and intermediate input use that potentially still contains input price variation. In addition to unobserved productivity, and a standard error term (ϵ), the production function also includes two price errors: (1) output price and (2) intermediate input price. Two observations are important to make. First we will obtain biased production function coefficients since it is very likely that input use (both in physical terms and in expenditure terms for materials) is correlated with output and input prices. Second, the estimate for productivity is obtained using biased coefficients and will

[25]Taking the results across both panels A and B together also suggests that the markups of minimills are expected to be higher since they still operate at lower marginal costs, due to higher productivity, as we control for prices.

furthermore also include output and input price variation. Without correcting for price variation, at both the input and output level, we would not correctly identify the productivity difference between minimills and integrated plants. In particular since we know that they rely on different intermediate inputs and produce different shares of the various products in the steel market.[26]

Fourth, 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 downward bias on the capital coefficient. Since VI plants are more capital intensive than minimills, this will again make VI plants appear more productive. When we correct for the simultaneity and selection biases in Columns III and VI using an investment control function correction, the capital coefficient is twice as large. Moreover, the minimill TFP premium doubles to an average effect of 11 percent, starting at 25 percent in 1963, but disappearing by 2002.

In all the subsequent analysis we rely on estimates of productivity, ω_{it} from Column VI of Table 6. However, technology does not explain all differences in productivity as the standard deviation of ω_{it} is about 30 percent, while differences in technology account for an 11 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 robust dispersion of productivity across producers in narrowly defined industries. See Syverson (2011) for a recent survey.

4.2 The Role of Reallocation

Following Olley and Pakes (1996) we consider industry-wide aggregate productivity as 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 $\overline{\omega}_{it} \equiv \frac{1}{N_t}\sum_i \omega_{it}$.

[26]Equation (5) also restates the findings of De Loecker, Goldberg, Khandelwal, and Pavcnik (2012), that only under the special case of a common and full pass-through, with a coefficient equal to the material input coefficient, will the use of undeflated revenue on input expenditures deliver the correct production function coefficients and an estimate for productivity, or formally if $p_{it} = \theta p_{it}^M$ and $\theta = \beta_M$.

4.2.1 Static Analysis: introducing a between technology covariance

In recent work, Bartelsman, Haltiwanger, and Scarpetta (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

$$\Omega_t = \overline{\omega}_t + \sum_i (\omega_{it} - \overline{\omega}_t)(s_{it} - \overline{s}_t) = \overline{\omega}_t + \Gamma_t^{OP} \tag{6}$$

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 particular decomposition will help us understand whether 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 $\bar{\omega}_t(\psi)$.[27]

Definition Within Technology Decomposition

$$\begin{aligned} \Omega_t &= \sum_{\psi \in MM,VI} s_t(\psi) \left(\overline{\omega}_t(\psi) + \sum_{i \in \psi} (\omega_{it} - \overline{\omega}_t(\psi))(s_{it}(\psi) - \overline{s}_t(\psi)) \right) \\ &= \sum_{\psi \in MM,VI} s_t(\psi) \left(\overline{\omega}_t(\psi) + \Gamma^{OP}(\psi)_t \right) \end{aligned} \tag{7}$$

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.[28]

[27] 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 $\sum_{\psi,i} s_{it}(\psi) > 1$.

[28] However, to asses the productivity effects within a type this rescaling by the type specific market share has no effect.

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 $\overline{\Omega}_t = \frac{1}{2}\sum_{\psi}\Omega(\psi)_t$, the industry productivity if minimills and vertically integrated producers had the same market share, i.e. the unweighted average, we obtain:

Definition Between Technology Decomposition

$$\Omega_t = \overline{\Omega}_t + \sum_{\psi \in MM,VI} (s(\psi)_t - 1/2)(\Omega(\psi)_t - \overline{\Omega}_t) = \overline{\Omega}_t + \Gamma_t^B \tag{8}$$

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. Notice 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 no matter the productivity difference between the two types.[29]

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

$$\Omega_t = \frac{1}{2}\sum_{\psi \in MM,VI} [\bar{\omega}_t(\psi) + \Gamma_t^{OP}(\psi)] + \Gamma_t^B \tag{9}$$

Notice that equation (9) allows us to explain changes in productivity, through either i) changes in the average productivity of minimills and vertically integrated plants ($\bar{\omega}_t(\psi)$), iii) changes in the covariance between output and productivity for both MM and VI plants ($\Gamma_t^{OP}(\psi)$), and iii) reallocation across technologies (Γ_t^B). Appendix D provides additional details.

4.2.2 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.

[29] Given the substantial entry of minimills who typically entered at a smaller scale, and remain 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.

Table 16 in the Appendix presents these cross-sectional analysis by 5 year period to provide more detail on the time-series of these decompositions.

Three important results emerge. First, the Olley-Pakes decomposition of aggregate productivity across all plants, shows the average producer became 15.5 percent more productive between 1963 and 2002. In addition, the reallocation towards more productive plants was an important process in generating higher productivity, generating a 7.5 percent increase from 1963 to 2002.[30] Thus aggregate productivity went up by 23 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 is -6.6 percent, as the older vintage of VI plants have both lower productivity and greater market share. The between covariance Γ^B then becomes less negative as the minimills, who have productivity premium, gradually increase their market share. Towards the end of the sample minimills have about half of the market which mechanically implies a zero between reallocation component. This between reallocation of output from VI plants to MM's accounts for a 6.3 percent increase in productivity, 27 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 lead to a sharp increase in productivity.

Third, drilling down to the technology type, we see that minimills increased their aggregate TFP ($\Omega(MM)$) by 10 percent, while vertically integrated plants raised their aggregate TFP ($\Omega(VI)$) by 24 percent. This "catching-up" of vertically integrated producers mirrors the results in Table 6: while vertical integrated producers were less productive than the minimills, by the end of the sample period, they almost completely caught up. Interestingly, the reason for this catch-up of vertically integrated producers is not due to changes in the Olley-Pakes covariance term $\Gamma^{OP}(\psi)_t$, whose contribution to productivity growth is is 5.2 percent for minimills and 5.3 percent for vertically integrated producers, but due to the much higher increase in average plant productivity for vertically integrated producers ($\overline{\omega}(VI)_{it}$) of 18.3

[30]Note that all the numbers are kept in logs as opposed to the original Olley-Pakes approach where an index was created since productivity was expressed in dollars.

percent, versus a $\overline{\omega}(MM)_{it}$ of 4.8 percent for minimills.

Our analysis so far points to a large role of minimills in shaping the overall industry productivity. We find that about 48 percent of total aggregate productivity growth can directly be attributed to minimills, with 27 percent due reallocation away from the old technology and the remaining 21 percent due to productivity improvements at minimill plants, which is capturing learning by doing taking place at minimills.[31]

4.2.3 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 10 year window: incumbents ($\mathcal{A}$), entrants ($\mathcal{B}$) and exiting plants ($\mathcal{C}$).[32] Using these sets, use equation (2) and consider aggregate productivity growth:

$$\begin{aligned}\Delta\Omega_t = & \underbrace{\sum_{i\in\mathcal{A}} s_{it-1}\Delta\omega_{it}}_{\text{Plant Improvement}} + \underbrace{\sum_{i\in\mathcal{A}} \Delta s_{it}\omega_{it-1} + \sum_{i\in\mathcal{A}} \Delta s_{it}\Delta\omega_{it}}_{\text{Reallocation}} \\ & + \underbrace{\sum_{i\in\mathcal{B}} s_{it}\omega_{it}}_{\text{Entrant}} - \underbrace{\sum_{i\in\mathcal{C}} s_{it-1}\omega_{it-1}}_{\text{Exit}}\end{aligned} \tag{10}$$

where the first term is denoted *Plant Improvement*, and the next two terms on are the *Reallocation* terms, 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 both types of technology separately we expand the above by computing equation (10) by technol-

[31] We do not pursue an explicit analysis of the learning by doing effects at minimills since our data does not contain the level of detail needed to credibly infer this process. See Benkard (2000) for such an analysis and what type of data is key to identify learning by doing.

[32] This decomposition has been suggested by Davis, Haltiwanger, and Schuh (1996) and has been used in other empirical work by e.g. De Loecker and Konings (2006).

ogy type ψ. When we refer to the total impact of reallocation we group all terms except the plant improvement component.

Table 8 presents the decomposition across all plants and by technology.[33] The first row of Table 8 restates the large productivity growth in the US steel sector of 23 percent, but far faster growth in productivity for vertically integrated plants than for minimills.[34]

Across the entire sample period in which productivity increased by 23%, improvements at plants caused a 10% increase in productivity, 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 within component of 14.7%, 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. However, reallocation and net entry play a small and negative role in TFP growth. For integrated producers the story is very different. While the plant improvement component of 10.2% is smaller than that of minimills (14.7%), the net entry term of 3.9% is almost 19 percent of total productivity growth over the sample, while the reallocation term of 11.8% is responsible for 48 percent of 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 are 4.4 percent more productive than those VI plants that exited the industry. New minimills, on the other hand, enter with no specific productivity advantage.

To summarize, we find a drastic difference in the role of reallocation between technologies. Whereas the productivity growth of minimills is entirely due to common within-plant productivity growth, integrated producers productivity growth is mainly coming from the reallocation of resources *across* producers (67 percent). In the next section, we will turn to the question of why the role of reallocation among vertically integrated producers was so important.

[33] We also analyzed the changes over a ten year period. Due to census disclosure rules we would not be able to present for shorter time windows, and the results are very similar.

[34] The numbers on the minimill and integrated need to be scaled by their relevant market share changes using $\Omega_t = \sum_\psi s_{t-1}(\psi)\Omega_t(\psi) + \Delta s_t(\psi)\Omega_{t-1}(\psi) + \Delta s_t(\psi)\Delta\Omega_t(\psi)$.

4.3 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, also spurred a dramatic reallocation process among the incumbent technology, where we showed that the exit margin played a key role. Our results also suggest that producers of the old technology, VI, were able to increase their productivity substantially as well.

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 using the old technology.

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*, are very different. Indeed, minimills take over bar products, but not sheet products. We therefore verify whether the substantial productivity gains among (surviving) VI producers over our sample period is related to the product market competition, i.e. did the VI producers of bar products exit, leaving only those VI producers specialized in sheet products.

The distinction between the two product groups is relevant to the extent that (1) there exists a productivity difference among bar and sheet producers, and (2) if survival is related to specialization.[35]

In order to verify whether this mechanism is important in the data, we first test whether plants specialized in *sheet products* are on average more productive, than those specialized 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 the product specialization can explain the rapid productivity growth among the group of VI producers.

Table 10 estimates both a technology and sheet specialization productivity pre-

[35] A potential third component would be the change in product specialization at the plant level over time. However, we found very little change in product specialization over time, and this mechanism therefore cannot generate within-plant productivity improvements. This finding sits well with our implicit assumption of plant-level productivity.

mium for a number of specifications, where sheet specialization refers to the share of a plant's revenue accounted for by sheet products.[36] In Panel A we consider all plants in the industry, and find a robust and highly significant productivity advantage for plants specialized in *sheet products*, while controlling for technology, and an exhaustive set of fixed effects. Even if we compare plants of the same technology, within the same firm and state, in the same year, we find a 12 percent productivity premium for plants completely specialized in sheet. In Panel B, we focus on the VI producers, and find a similar premium. These results, therefore, strongly 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 indeed VI producers primarily producing sheet products have a higher likelihood of survival. In Table 6, we present survival regressions, where we run an indicator of plant survival – whether a plant which was active in 1963, survives until 2002 – against plant technology and sheet specialization.[37] 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, while holding fixed its technology. Indeed, a plant that is fully specialized in sheet has a 31 percent higher probability of surviving than a plant that is fully specialized in bar. This is a very large effect as plants have 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.[38] In Panel B, we focus on VI producers and find a very similar effect: VI producers specialized in sheet products in 1963 have a 31 percent higher probability of surviving to the year 2002. We note that predicting plant survival over a 40 period is a very demanding task. Even when our sample size is reduced to the 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.

[36]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. 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 premia of sheet producers.

[37]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.

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

The joint productivity and survival premium thus 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 is 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, 34 percent of the industry's productivity growth is due to the reallocation process among VI producers, in which the specialization in *sheet products* seem to have played a crucial role. To obtain the 34 % contribution, we use the fact that 67% of the VI productivity growth was due to reallocation (Table 8). To find the contribution of this reallocation component in total productivity growth we use the identity that $\Delta\Omega = \frac{1}{2}(\Delta\Omega(VI) + \Delta\Omega(MM)) + \Delta\Gamma^B$. Thus a 67 share of reallocation will increase $\Delta\Omega$ by $0.5 * 0.235 * 0.67 = 0.078$, which is about 34% in overall productivity growth (0.078/0.23).

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 accounts for only 13% 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. Put another way, it would be surprising if 40 years of innovation in the engineering and management of vertically integrated plants had not manifested itself in increased productivity. Still, this means that 87 percent of total productivity growth can be attributed to the reallocation induced by minimill entry.

4.4 Market Power and Reallocation

The drop in demand for US steel producers and the variation in the market shares trajectories across products points to drastic changes in competition. Indeed we have argued that the entry of the minimill intensified competition for domestic steel producers. 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 affect a plant's residual demand curve and therefore impact its ability to charge a price above marginal cost. Moreover, the change in the residual demand elasticity, and its associated markup response, are expected to affect the reallocation across producers as well.

We rely on our empirical framework to (1) show that markups indeed decreased as competition increased, and (2) we discuss 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 our approach is that we can generate measures of competition from our estimates of the production function. We rely on our production function framework to recover markups by technology type and plant. In order to obtain markups from the plant-level production data we follow the approach suggested by De Loecker and Warzynski (2012) and we refer to the appendix for the details of that approach. At the core of this approach lies the assumption that plants minimize costs and that at least one input of production faces no adjustment costs.

The two main ingredients into computing markups are the output elasticity of intermediate inputs, such as materials and energy, and the corresponding expenditure share of the input. The latter are directly observed in the data, whereas the output elasticities are recovered after we estimate the production function as discussed above.[39]

We compute markups by technology as obtained from technology specific aggregate expenditures on an intermediate input ($E_t(\psi)$), materials in our case, and sales ($R_t(\psi)$) while relying on a time invariant Cobb-Douglas output elasticity of the intermediate input (β_m):

$$\mu_t(\psi) = \beta_m \frac{R_t(\psi)}{E_t(\psi)} \tag{11}$$

Under the commonly assumed Cobb-Douglas production function these markups are in fact the correct technology specific markups, where the markup by technology can be thought of as a weighted average across plants where the weights are the expenditure share on materials of a given plant in the total expenditure for plants of the same technology.[40] Figure 4 plots the markup trajectory over 40 years for both MM and VI plants. Markups have steadily decreased over time and are consistent

[39] 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 implication on 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.

[40] 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: $\mu_t(\psi) = \sum_{i\in\psi} c_{i\psi t}\mu_{it} = \sum_{i\in\psi} c_{i\psi t}\beta_m \frac{R_{it}}{E_{it}} = \beta_m \frac{R_t(\psi)}{E_t(\psi)}$.

with the drop in prices and external measures of concentration reported for the steel sector.[41] Markups are on average higher for minimills, confirming the results from the augmented production function estimation in Table 6.

It is interesting to note that markups fall at the same time as the covariance between output and productivity increases. Suppose that this fall in markups is due to firm's residual demand curve becoming more elastic. In other words, markups fall because the product market for steel becomes more competitive. This does not seem unlikely since import competition has risen from 5 to over 40 percent of domestic consumption, and there are far more steel producers in 2002 than 1963.

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 addition to the increased import competition. A similar point is made, in the context of variable markups and trade liberalization, by Edmond, Midrigan, and Xu (2012) and Mayer, Melitz, and Ottaviano (2011). Thus we expect the extent of competition to be directly linked to reallocation, which is what we find in the data.

4.5 Collecting Our Results

We find that the diffusion of minimills has a large impact on the steel industry. First, minimills diffuse slowly throughout the industry. In 1963 they represent less than 5 percent of the industry's output, rising to over 40 percent in 2002. However, this diffusion differs by product segment, as minimills produce 60 percent of bar products in 1990, but only 15 percent of sheet products.

Second, we find that minimills are substantially more productive than vertically integrated plants. This difference in productivity is masked by price changes, since the products produced by minimills, which are primarily bar products, have prices that fall by about 10 percent more than the prices of products produced by vertically integrated producers (mainly bar and sheet products). These price changes are enormous, as the 30 percent increase in productivity in the industry is concurrent with a 40 percent fall in prices for steel products.

Third, reallocation, either on the intensive margin or the extensive margin of

[41] The trajectory of markups in itself warrants attention and has been at the core of outstanding debate on the role of monetary policy and whether markups are pro or countercyclical. We see this as important by-product of our setting and approach.

entry and exit, explains a large share of productivity growth in this industry from 1963 to 2002. However, reallocation has vastly different effects for minimills and vertically integrated plants. Indeed, reallocation plays no role in the productivity growth of minimills, while for vertically integrated plants, reallocation is responsible for 66 percent of it. Thus, as one might expect, the process of creative destruction is important for the the older technology.

However, this reallocation among the VI can also be attributed to minimills. We find that the majority of the improvements in productivity among the vertically integrated producers are driven by the exit of VI bar producers, who competed directly with minimills. As VI sheet producers are 10 percent more productive than VI bar producers, this exit process increased TFP among vertically integrated plants.

Third, the industry has periods with a negative covariance between output and productivity. This pattern is difficult to explain, since almost any model would predict that more efficient plants would grow more than less efficient ones. However in steel, the old technology of vertically integrated plants has a much larger minimum efficient scale, and these plants are on average four times larger than minimills. Thus the observed negative covariance is due to the fact that vertically integrated producers are both bigger and less productive than minimills.

Finally, we find markups fall from about 1.3 in 1967 to around 1 in 2002. As these markups are tightly linked to the elasticity of the residual demand curve, we see falling markups as evidence of increased competition in the industry which lead to reallocation.

5 Alternative explanations and Robustness Analysis

In this section we explore various alternatives that can potentially help explain the sharp increase in productivity growth. It is important to note that none of these alternatives are mutual exclusive. The point of this section is not to argue that *only* technology was responsible for bringing about the efficiency gains. We show that our main results are not affected by controlling for these alternative explanations: firm-level characteristics, geography, and international trade do not appear to play a role in explaining either the differences in productivity between minimills and vertically integrated producers, nor the reallocation between these technologies.

Finally, we present the main results from our decomposition analysis using a

variety of productivity estimates (as presented in Table 6). We discuss both the robustness of our results, and highlight the importance of our corrections in establishing a prominent role of technology in generating aggregate productivity growth.

5.1 Management practices and ownership

Our analysis thus far has been on plants. To the extent that better plants are managed by better firms, we are potentially attributing productivity differences across plants to technology, where it might simply reflect 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 explaining productivity differences is in particular plausible given the recent evidence put forward by Bloom and Van Reenen (2010). They present empirical evidence that measures of productivity, like the one we use, are correlated with various management practice, reflecting human resource (HR) practices and organizational design. As well, Ichniowski, Shaw, and Prennushi (1997) find that better HR practices lead to higher productivity using detailed product-line data.[42] Their results confirm recent theoretical models which stress the importance of complementarities among work practices.

To check whether the minimill premium is not driven by better managed firms, or *any* particular kind of firm specific ownership structure, we compare minimills to VI plants *within* the same firm and time period using the following regression:

$$\omega_{ift} = \gamma_{ft} + \gamma 1(\psi_{if} = 1) + \epsilon_{ift} \tag{12}$$

where f indicates the firm that the plant i is owned by, and we rely on our estimates of plant-level productivity in Table 6. Table 12 presents these results. We start out in column I with a base premium of 10 percent. We find almost an identical productivity premium, of around 10 percent, for minimills when including a firm-time fixed effect γ_{ft} (column II).

These results suggest that the minimill productivity premium is not driven by a particular allocation of minimill plants to more productive firms with, say, better management or human resource (HR) practices. Moreover, our results do not contradict those presented by Ichniowski, Shaw, and Prennushi (1997), who rely on a sample of 17 rolling mills collocated with vertically integrated plants in the United

[42]The plants investigated by Ichniowski, Shaw, and Prennushi (1997) are rolling mills associated with vertically integrated producers, which are omitted from our analysis.

States, and therefore omit minimills from the analysis. Thus there is no information on the relative performance of minimills. In addition, they focus on rolling operations which we purposefully leave out.[43]

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 very unlikely, it would take historical plant-level data on management to rule it out, and Census data during our sample period unfortunately does not track this type of information.[44]

5.2 Geography

Although production of steel has historically been concentrated in a few regions in the US, there is still considerable variation of activity across regions. In 2002, 63 percent of steel is 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, where r denotes a state, in a regression of productivity on our measure of technology. Table 12 lists estimates of the following regression:

$$\omega_{irt} = \gamma_{rt} + \gamma 1(\psi_{if} = 1) + \epsilon_{irt} \tag{13}$$

The substantial minimill premium is largely unaffected when including state-time fixed effects. This result reflects that minimills, are on average 12.9 percent more productive than integrated producers in the same state and year (column III). This result is furthermore 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 25 percent. 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 12 indicate that the

[43]The main reason to omit rolling mills is because the boundary between rolling operations and other steel shaping operations, such as say pipe making or other more artisanal iron work, are blurry. By focusing on the production of molten steel, we obtain more well-articulated definition of the industry.

[44]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.

productivity premium for minimills is extremely robust, and is not an artifact of a particular selection mechanism at the firm or regional level, or an interplay of both.

5.3 International Trade

It is well documented that the US steel sector faced stronger competition from foreign producers over the course of the last four decades. However, for our purposes the relevant question is whether the mere increase in import competition could explain the rapid productivity growth in the industry.

Table 13 lists the average productivity growth and import penetration ratio across the US manufacturing industries (4 digit SIC codes), and compares them with the steel industry. The upper panel lists the absolute imports and shows that the steel sector's imports did not increase nearly as much as the modal manufacturing industry. The bottom panel report the import penetration ratio, and likewise, finds that an increased role of imports over the time period, but far less growth other parts of manufacturing.[45] This table highlights that international competition increased across all US manufacturing industries, and that steel was no exception. However, both in an unweighted and weighted sense, the change in the international competition in US steel was lower than the average for manufacturing. Productivity growth in the steel industry, as documented previously in Table 1, is three times higher than the average. While we see increased import competition for domestic steel producers, by itself, this cannot explain the exceptional improvements in productivity.

Using the statistical relationship between productivity growth and the change in the import penetration ratio, over the period 1972-1996, we would only predict an 8 percent productivity growth for the steel industry.[46] Put differently: the change in international competition can at most only explain about one third of the productivity growth.

These types of estimates are further subject to various biases and measure-

[45] The import penetration ratio is calculated in the usual way as: [imports/(domestic production - exports)].

[46] We construct a matched production-trade database at the 4 digit SIC87 level using the NBER Manufacturing Database and the US Trade Database. We consider a simple long difference regression of TFP growth on the change in the import penetration ratio. The estimated coefficients are used to predict the steel industry's productivity growth. Specifically we run the following regression: $\Delta\Omega_I = \gamma_0 + \gamma_1 \Delta IPR_I + \nu_I$ across the entire sample of 4 digit SIC87 industries, where Δ is the difference over the 1972-1996 period, and we weigh observations by the industry's share in total manufacturing production.

ment problems. For instance the Semiconductor industry experienced remarkable productivity growth, while its import penetration ratio increased only moderately. However, the latter was mostly imports from US producers outsourcing production while focusing on R&D and design in the US affiliates.[47] Identifying the impact of foreign competition on industry performance is further complicated due to endogenous changes in international competition as well as reversed causality from productivity growth to international trade.

In this paper we focus on a clean and directly measurable source of productivity growth: the arrival of a new technology. The potential role of international trade in affecting productivity growth indirectly is further weakened since the specific trajectory of imports, or any alternative measure of international competition, is not aligned with the arrival of the new technology. We do acknowledge, as shown in Table 9, that changes in international competition did most likely affect domestic producers by shifting in the residual demand for steel products. In this sense the increased competition introduced by minimills was reinforced, if anything, by competing over a smaller market share, a mechanism we account for in our analysis of markups.

Finally, one might still worry that the effects of international competition were more pronounced for integrated producers than for minimills, thereby affecting the interpretation of our results. Therefore, we checked whether the measures of international competition, such as import shares, differ across products. As discussed previously, minimills were mainly active in the bar segment, especially in the period 1972-1996 where we observe good measures of international competition (also see Figure 2). When we break down imports and exports by product, we find that imports show a similar rise for bar products produced by minimills as for the sheet products, which minimills do not produce. Thus it is not possible for us to identify a differential role of international competition on the reallocation from VI to MMs.

5.4 Robustness and Importance of Corrections

Table 9 presents robustness checks on our main decompositions of aggregate productivity growth. For each of the productivity regressions in Table 6, we produce the static and dynamic decompositions in Tables 7 and 8, and show the share of productivity growth which is accounted for by different decompositions.

More specifically, we list our main results in the first column and those were in

[47] See Samuels (2012) and also Jorgenson, Ho, and Stiroh (2008).

fact obtained using the production function coefficients of specification VI in Table 6. We contrast these to results obtained using productivity estimates obtained without correcting for unobserved price differences across producers (III), and to results obained without correcting for unobserved productivity (I and IV). There are two important takeaways from this table.

First of all, we find that our decompositions are qualitatively robust to alternative specifications of the production function. We find similar differences in the speed of productivity growth between technologies, a far larger role for reallocation among the vertically integrated producers than the minimills, and a large role for the between covariance in productivity growth.

Secondly, the results in Table 9, however, also clearly point out the importance of correcting for unobserved productivity and price errors when estimating the production function, to obtain the correct quantitative effects of the entry of minimills on aggregate productivity. What is in particular sensitive to the specification of the production function is, as expected, the *between* decomposition. This is not too surprising, as Table 6 showed that the minimill productivity premia was far larger in Column VI (GMM and price correction), than in Column I (OLS). These difference in the estimated productivity advantages of minimills directly spill over to the estimated magnitude of the between covariance.

In other words, if we were to incorrectly ignore 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. The role of entry and exit is, again as expected, largely affected by not correcting for price and productivity errors in the production function. The impact of the exit process of integrated producers is almost cut in half (from 19% to 8%), while within-plant minimill improvements are underestimated substantially as well (107% versus 79%). We would thus underestimate both the reallocation among integrated producers, induced by minimill entry, and the reallocation between technologies, leading to a substantial underestimation of the total impact of the arrival of the new production technology.

Our results suggest that the total effect of minimill entry on industry-wide productivity growth was about 87%. This share drops to about 72 % when ignoring unobserved price and productivity heterogeneity. However, although we find a much bigger magnitude, the role of technology is still large when using uncorrected productivity estimates, which adds to the robustness of our specific reallocation mechanism: the arrival of a new technology.

6 Conclusion

There is extensive evidence that large gains in productivity can be attributed to reallocation of resources towards more productive plants. This paper is one of the first to provide a specific mechanism underlying such a reallocation. We show that the entry of a new technology, and its associated increased competition, were responsible for a large share of the massive productivity growth in the US steel industry.

In particular, we put forward evidence that technological change can 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 lead to a slow but steady drop in the market share of the incumbent technology, the vertically integrated producers. As minimills were 11 percent more productive, this movement of market share between technologies is responsible for a third of productivity growth in the industry.

Second, while the new technology started out with a 25 percent productivity premium, by the end of the sample, minimills and vertically integrated producers are very similar in terms of efficiency. This catching-up process of the incumbents came about from a large *within* reallocation of resources among vertically integrated plants. This reallocation among vertical integrated plants was largely due the exit of inefficient producers active in the low quality segment (bar products.) On the other hand, minimills productivity grew moderately, and entirely due a common shift in the production frontier.

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TABLES AND FIGURES

Table 1: Relative Performance of the steel sector

Sector	Δ TFP	Δ Shipments	Δ Labor
Steel Sector	28%	-35%	-80%
Mean Sector	7%	60%	-5%
Median Sector	3%	61%	-1%

Source: NBER-CES Dataset for SIC Code 3312. Note: Only sectors over 10 billion dollars are included. Changes computed between 1972-2002.

Table 2: 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 3: 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 ships 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 4: 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).

Table 5: 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	Exitors
1963-1972	17	D∗
1973-1982	39	0
1983-1992	43	26
1993-2002	D∗	17
Vertically Integrated	Entrants	Exitors
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.

Table 6: Production Function

Dep Variable	Panel A: Output Deflated by Steel Price Index			Panel B: Output Deflated by Product Prices		
	I	II	III(GMM)	IV	V	VI (GMM)
Labor	0.329	0.326	0.266	0.326	0.324	0.261
	(0.013)	(0.013)	(0.024)	(0.013)	(0.010)	(0.036)
Materials	0.613	0.616	0.658	0.632	0.634	0.683
	(0.011)	(0.011)	(0.031)	(0.010)	(0.011)	(0.038)
Capital	0.054	0.055	0.093	0.054	0.055	0.091
	(0.009)	(0.009)	(0.020)	(0.009)	(0.009)	(0.020)
VI (alone)	-0.028		-0.080	-0.062		-0.111
	(0.017)		(0.037)	(0.017)		(0.039)
VI		-0.098	-0.198		-0.124	-0.246
		(0.031)	(0.074)		(0.031)	(0.077)
VI		0.003	0.006		0.003	0.006
× Year		(0.001)	(0.003)		(0.001)	(0.003)
Year FE	X	X		X	X	
Constant	-0.618	-0.577	-0.776	-0.655	-0.620	-0.802
	(0.051)	(0.071)	(0.025)	(0.071)	(0.072)	(0.025)
R^2	0.97	0.97		0.97	0.97	
Observations	1499	1499	1499	1499	1499	1499

Note: GMM indicates a two-stage investment control function procedure with a selection adjustment was used. More detail on this procedure is provided in Appendix E.1. In Column III and VI, the **VI (alone)** term is estimated by projecting estimating productivity on an indicator for a vertically integrated plant, while the **VI** and **VI** × **year** term indicates the same projection with an additional year interaction term. Standard errors are clustered at the plant-level to control for heteroskedasticity and serial correlation. For columns III and VI this clustering is computed via block bootstrap which in addition corrects for the multi-step nature of the GMM estimator.

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

Aggregate TFP $\Delta\Omega$	23.0%	
Olley-Pakes Decomposition:		
Unweighted Average: $\Delta\overline{\omega}$	15.5% (0.67)	
Covariance: $\Delta\Gamma^{OP}$	7.5% (0.33)	
Between Decomposition:		
Unweighted Average: $\Delta\overline{\Omega}$	16.8 % (0.73)	
Between Covariance: $\Delta\Gamma^{B}$	6.3 % (0.27)	
Within Decomposition:	Minimills	Integrated
Aggregate TFP: $\Delta\Omega(\psi)$	10.0%	23.6%
Unweighted Average: $\Delta\overline{\omega}(\psi)$	4.8% (0.48)	18.3% (0.78)
Within Covariance: $\Delta\Gamma^{OP}(\psi)$	5.2% (0.52)	5.3% (0.22)

Table 8: Dynamic Decomposition of Productivity Growth

Component	All	Minimill	Integrated
Total Change	23.0%	10.0%	23.6%
		(0.21)	(0.52)
Plant Improvement	10.2%	14.7%	10.2%
		(0.23)	(0.17)
Reallocation	10.6%	-1.5%	11.8%
		(-0.1)	(0.25)
Net Entry	3.9%	-0.8%	3.9%
		(0.0)	(0.10)
Entry-Exit Premium		0.0%	4.4%

Note: The share of each component in the total aggregate productivity growth is listed in parantheses. See equation (10) for definitions of various terms.

Table 9: Decompositions under Alternative Productivity Measures

	Specification in Table 6			
	VI	III	I	IV
Change in TFP ($\Delta\Omega$)	0.23	0.25	0.31	0.30
Olley-Pakes				
Unweighted Average ($\Delta\overline{\omega}$)	67%	74%	74%	69%
Covariance ($\Delta\Gamma^{OP}$)	33%	26%	26%	31%
Between				
Change in $\overline{\Omega}$	73%	78%	89%	87%
Change in Between Technology Covariance ($\Delta\Gamma^{B}$)	27%	22%	11%	13%
Within Technology				
Minimills				
Change in TFP (ratio to aggregate $\frac{\Delta\Omega(MM)}{\Delta\Omega}$)	0.43	0.50	0.77	0.74
Fraction from Unweighted Average ($\Delta\overline{\omega}(MM)$)	48%	71%	70%	61%
Fraction from Covariance ($\Delta\Gamma^{OP}(MM)$)	52%	29%	30%	39%
Vertically Integrated				
Change in TFP (ratio to aggregate $\frac{\Delta\Omega(VI)}{\Delta\Omega}$)	1.03	1.05	1.01	0.99
Fraction from Unweighted Average ($\Delta\overline{\omega}(VI)$)	77%	85%	82%	75%
Fraction from Covariance ($\Delta\Gamma^{OP}(VI)$)	23%	15%	18%	25%
Dynamic Decomposition				
All				
Plant Improvement	34%	41%	46%	41%
Reallocation	47%	43%	40%	42%
Entry-Exit	19%	16%	14%	16%
Minimills				
Plant Improvement	107%	119%	90%	79%
Reallocation	-9%	-12%	-1%	4%
Entry-Exit	0%	-6%	11%	18%
Vertically Integrated				
Plant Improvement	33%	39%	43%	40%
Reallocation	47%	46%	49%	50%
Entry-Exit	19%	15%	8%	10%

Table 10: 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	-0.126	-0.138	-0.167	-0.127	-0.295					
	0.022	0.026	0.020	0.044	0.087					
Sheet Specialization		0.101	0.121	0.118	0.119	0.099	0.128	0.122	0.165	0.127
Ratio		0.038	0.027	0.042	0.068	0.046	0.039	0.059	0.106	0.081
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	657	657	657	657	657
Number of Fixed Effects	301	301	289	914	129	124	175	353	124	540
R^2	0.041	0.104	0.056	0.022	0.056	0.077	0.022	0.014	0.060	0.021
F	32.428	16.086	35.701	6.575	6.042	6.460	10.585	4.295	3.686	2.455

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 11: 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	0.33
		(0.03)		(0.24)	(0.26)
Productivity (ω)		0.04			0.06
		(0.14)			(0.04)
Observations	128	128	78	78	78
Log-Likelihood	-73.88	-73.69	-40.36	-40.02	-38.88
$\chi 2$	16.97	17.35	5.89	6.58	8.84
Baseline Probability	0.33	0.32	0.23	0.23	0.22

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

Table 12: Technology Premium: Robustness Checks

	I	II	III	IV	V	VI	VII	VIII	IX
VI	-0.108	-0.098	-0.129	-0.253	-0.184	-0.126	-0.203	-0.457	
	0.022	0.043	0.018	0.084	0.040	0.075	0.035	0.174	
VI × Year					0.004	0.001	0.004	0.008	0.002
					0.002	0.003	0.001	0.006	0.001
Fixed Effect									
Year	X				X				X
Year-Firm		X				X			
State-Year			X				X		
Firm-Year-State				X				X	
Plant									X
Observations	1498	1498	1498	1498	1498	1498	1498	1498	1498
Groups	301	914	289	1291	301	914	289	1291	301
R^2	0.093	0.009	0.040	0.042	0.098	0.009	0.045	0.050	0.065
F	16.962	5.254	50.605	8.994	16.064	2.726	28.525	5.410	9.146

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

Table 13: International Competition: Comparing the Steel Sector to US 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 4 digit SIC87 industries using data provided by the NBER Manufacturing Database (for shipment data) and Schott for import penetration data. The changes are computed by industry before taking averages. The import penetration rate data is only available up to 1996. Weights are based on the industry's share of shipments in total manufacturing shipments as recorded in the NBER Manufacturing Database.

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

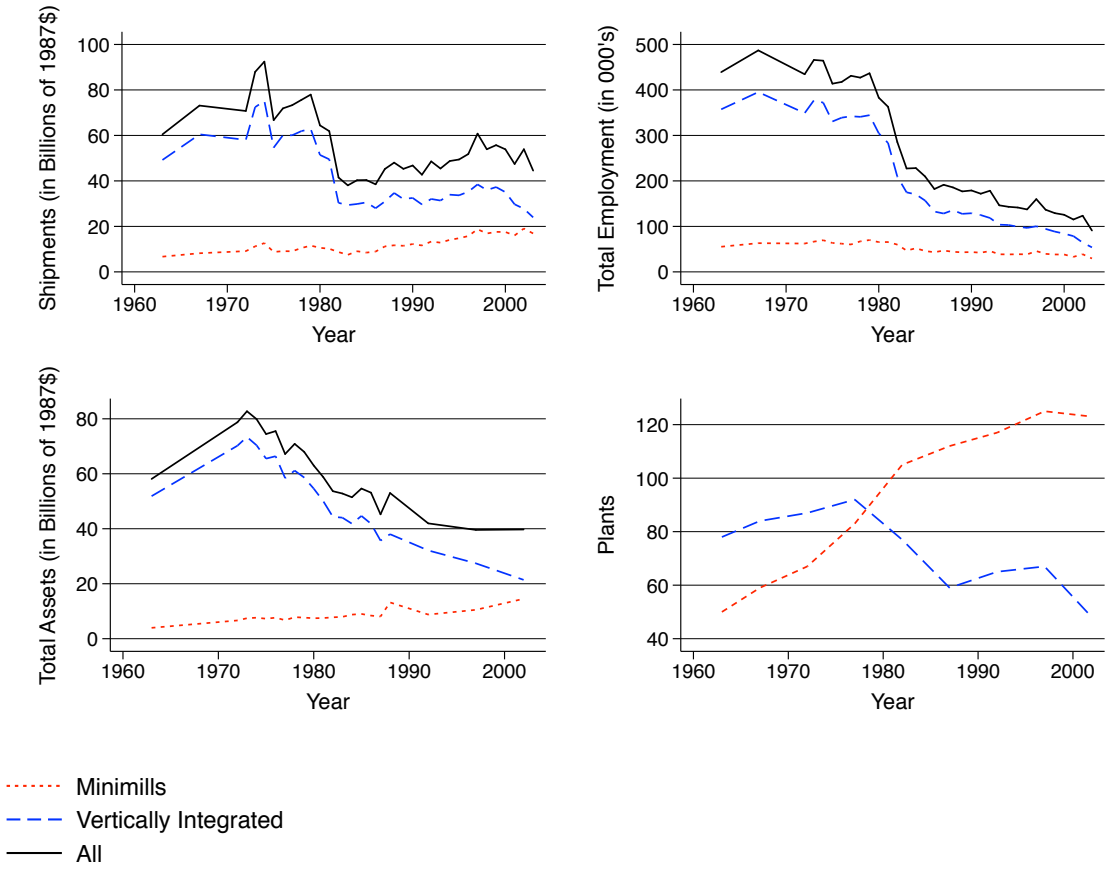


Figure 2: Minimills Market share by Major Product.

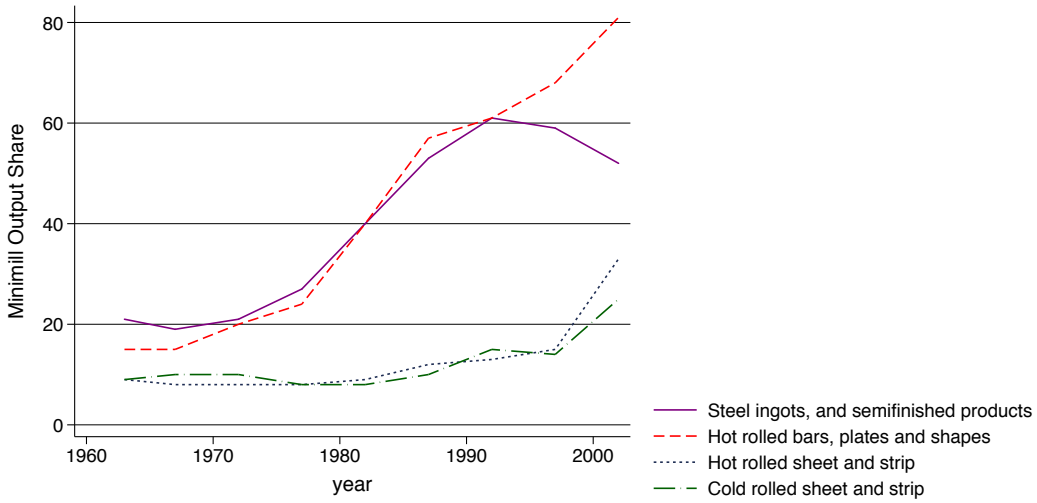
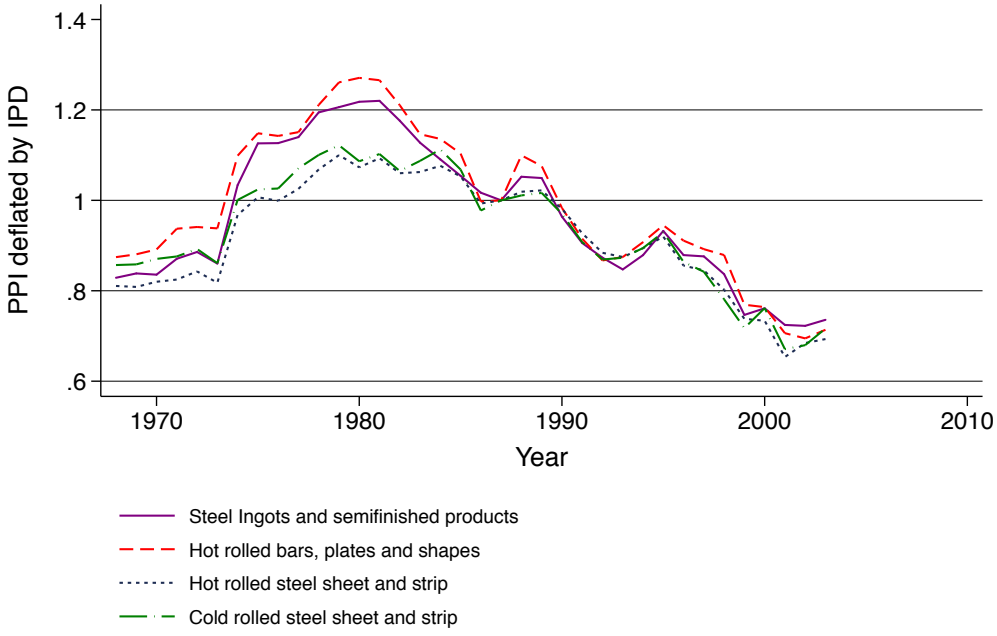
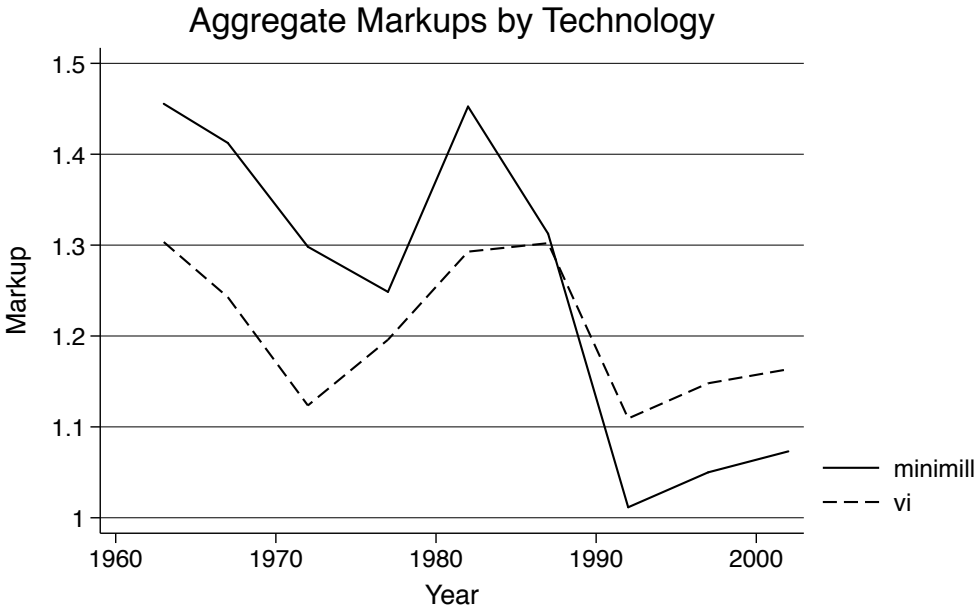


Figure 3: Producer Output Price Index by Product Segment



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

Figure 4: Market Share Weighted Markups



Source: Own calculations using US Census data.

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.[48] Therefore, we only include a plant in the sample 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 either minimills, vertically integrated or rolling and processing plants.

The 2007, 2002 and 1997 Census of Manufacturing have a special inquiry questionnaire for the steel industry (henceforth SI) appended to it. This questionnaire asks plants if they are considered to be 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 which 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.[49]

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 are 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.

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

[49] For references on the differences between minimills and vertically integrated plants, see Fruehan (1998) p.1-12, Crandall (1981) p.5-15.

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% of a plant's material use, we flag this plants as a minimill.[50]

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" in other words, steel ingots and so on that are shaped into steel products.

We also use the product trailer to categorize plants. If a plant produces "Coke Oven or Blast Furnace Products" we flag this plant as a vertically integrated. As well, 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 80's. For references on the changing ability of minimills to produce sheet products, see Rogers (2009) page 162 and chapter 8 of Hall (1997).

Plants are not always consistently coded 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% of the time. Likewise, a plant is assigned to the minimill category if it is flagged as such at least 80% of 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 shown in Table 14. These are responsible for 93 percent of output not categorized as "other" or "unclassified" in 1997.

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

Product	Product Codes
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

Table 14: Description of Product Codes

B Additional Tables and Figures

Table 15: Growth of Market Share for Minimills and Vertically Integrated Plants

	Industry-wide Growth Rate of:				
Year	**Shipments**	**Employment**	**Capital**	**Materials**	**TFP**
1963-1967	20	10	.	25	5
1967-1972	-2	-11	.	7	-5
1972-1977	3	-2	-16	-2	-1
1977-1982	-56	-40	-22	-64	-6
1982-1987	8	-42	-17	9	11
1987-1992	7	-6	-7	26	7
1992-1997	23	-12	-8	20	16
1997-2002	-20	-34	-5	-21	0
		Minimills:			
1963-1967	0	0	.	0	2
1967-1972	2	1	.	1	2
1972-1977	0	0	2	1	4
1977-1982	9	7	5	8	10
1982-1987	4	5	4	6	8
1987-1992	3	1	3	5	1
1992-1997	3	3	6	3	1
1997-2002	8	6	13	8	7

Table 16: Decomposing Productivity Growth: Within and Between Technology (1963-2002)

Panel A: All Plants and Between Technology

	All			Between		
year	Aggregate	Average	Covariance	Market Share	Average	Covariance
1963	-0.107	-0.025	-0.082	0.120	-0.042	-0.066
1972	-0.190	-0.121	-0.069	0.135	-0.142	-0.055
1977	-0.096	-0.087	-0.009	0.131	-0.074	-0.022
1982	-0.044	-0.016	-0.028	0.223	0.000	-0.048
1987	0.035	0.062	-0.027	0.265	0.069	-0.034
1992	-0.033	-0.034	0.001	0.294	-0.009	-0.021
1997	0.097	0.068	0.029	0.328	0.103	-0.006
2002	0.123	0.130	-0.007	0.407	0.126	-0.003
Change	0.230	0.155	0.075	0.287	0.168	0.063
Share		67%	33%		73%	27%

Panel B: Within Technology

	Minimills			Integrated		
year	Aggregate	Average	Covariance	Aggregate	Average	Covariance
1963	0.044	0.103	-0.059	-0.128	-0.107	-0.021
1972	-0.065	-0.054	-0.012	-0.218	-0.179	-0.039
1977	-0.045	-0.040	-0.005	-0.103	-0.129	0.026
1982	0.087	0.059	0.028	-0.087	-0.125	0.038
1987	0.142	0.101	0.042	-0.004	-0.010	0.006
1992	0.043	-0.004	0.047	-0.060	-0.082	0.022
1997	0.120	0.072	0.048	0.086	0.061	0.025
2002	0.144	0.151	-0.007	0.108	0.076	0.032
Change	0.100	0.048	0.052	0.236	0.183	0.053
Share	-	48%	52%	-	78%	22%
Share Average	21%	10%	11%	52%	40%	12%
Share Overall	23%	21%	2%	77%	61%	16%

Note: All the entries are in logs. Summing the market share weighted technology specific aggregate productivity measures results in the numbers listed under the Aggregate column of All plants in Panel A. For example for the year 2002 the aggregate productivity term is 0.123 and this is given by $(0.144 * 0.407) + (0.108 * 0.593)$. The market share by technology is listed in Panel A. The *Share Average* entries in Panel B reflect the share of the relevant component in the between average component listed in Panel A. For instance the *Share Average* of minimills, 10%, is obtained using $0.5 * 0.048/0.23$. The four components, average and covariance by technology, sum up to the share of the between average share in Panel A, i.e. 73%. The *Share Overall* entries in Panel B are obtained by multiplying the specific component (average and covariance) by the relevant market share. For example the share of the minimills within productivity growth term in the overall aggregate productivity growth (of 21%) is obtained as follows: $(0.151 * 0.407 - 0.103 * 0.12)/0.23$. As mentioned in the text if the market shares are equal (at 0.5) the between covariance is zero by construction, and it would also imply that the technology specific aggregate productivity would simply be 1/2 of the industry's aggregate productivity. We omit census year 1967 due lack of reliable capital stock data for that year.

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).[51]

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:

$$Q_{ijt} = X_{ijt}\Omega_{it} \tag{14}$$

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, $X_{it} = L^{\beta_l}K^{\beta_k}M^{\beta_m}$.

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

$$R_{it} = \sum_j X_{ijt}\Omega_{it}P_{jt} \tag{15}$$

To recover plant-level productivity from a regression of plant-level (deflated)

[51] Specifically, we use the following BLS price series:

Series ID	Product
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
PCU331111331111F	Cold finished steel bars

revenues and input use, we use:

$$X_{ijt} \equiv s_{ijt} X_{it} \tag{16}$$

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

$$R_{it} = \Omega_{it} X_{it} \sum_j s_{ijt} P_{jt} \tag{17}$$

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

$$\frac{R_{it}}{\sum_j s_{ijt} P_{jt}} = X_{it} \Omega_{it} \tag{18}$$

or in logs:

$$r_{it} - \tilde{p}_{it} = \beta_l l_{it} + \beta_k k_{it} + \beta_m m_{it} + \omega_{it} + \epsilon_{it} \tag{19}$$

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 a 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 (19) to the data we need to take a stand on the input allocation or what s_{ijt} is. We use revenue shares:

$$s_{ijt} = \frac{R_{ijt}}{\sum_j R_{ijt}} \tag{20}$$

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 is obtained using the FOC on input X of cost minimization:

$$\mu_{ijt} = \beta^X \frac{R_{ijt}}{P_t^X s_{ijt} X_{it}} \tag{21}$$

We directly assumed that all plants face common input prices, P_t^X, for a given input X. Now using equation (20) we get the following expression for markups:

$$\mu_{ijt} = \beta^X \frac{R_{it}}{P_t^X X_{it}} \tag{22}$$

which highlights that $\mu_{ijt} = \mu_{it}$ and $\forall j \in J_i$.

Note that the reason we need to restrict markups across products, within a

plant, to be constant is due to the fact that we only see aggregate input use at the plant level.[52] 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 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 we can directly be used 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.

C.2.2 Intermediate inputs

The data on intermediate input use, m_{it}, 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, i.e. 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 therefore worried that the aggregate deflator does not capture fully 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)}.

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

[52] See De Loecker and Warzynski (2012) and De Loecker, Goldberg, Khandelwal, and Pavcnik (2012) for a detailed discussion of the input allocation across products.

$$P_{it}^M = \sum_n s_{it}^n P_t^n \tag{23}$$

$$s_{it}^n = \frac{M_{it}^n}{\sum_n M_{it}^n} \tag{24}$$

$$P_t^n = N^{-1} \sum_i P_{it}^n \tag{25}$$

In words we compute the average price for a given input n, P_t^n, and weigh this by the plant's input share s_{it}^n. 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 (25) 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 is 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 $m_{it} = \ln\left(\sum_n \frac{M_{int}}{P_{it}^M}\right)$.

D 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:

$$\Omega_t = \sum_i s_{it}\omega_{it} \tag{26}$$

where we define:

$$s_{it} = \frac{R_{it}}{\sum_i R_{it}} \tag{27}$$

$$R_t = \sum_i R_{it} \tag{28}$$

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

D.1 Standard OP

Olley and Pakes show that (26) can be written as:

$$\Omega_{it} = \bar{\omega}_t + \sum_i (s_{it} - \bar{s}_t)(\omega_{it} - \bar{\omega}_t) \tag{29}$$

$$= \bar{\omega}_t + \Gamma_t^{OP} \tag{30}$$

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

$$\bar{\omega}_t = N^{-1} \sum_i \omega_{it} \tag{31}$$

$$\bar{s}_t = N^{-1} \sum_i s_{it} \tag{32}$$

D.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 (26) and simply break up the sum into the two technology types, i.e. $\psi = \{MM, VI\}$:

$$\Omega_t = \sum_{i \in \psi = MM} s_{it}\omega_{it} + \sum_{i \in \psi = VI} s_{it}\omega_{it} \tag{33}$$

$$= s_t(\psi = MM) \sum_{i \in \psi = MM} \frac{s_{it}}{s_t(\psi = MM)} \omega_{it} \tag{34}$$

$$+ s_t(\psi = VI) \sum_{i \in \psi = VI} \frac{s_{it}}{s_t(\psi = VI)} \omega_{it} \tag{35}$$

$$\tag{36}$$

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

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

$$\Omega_t = \sum_{\psi} s_t(\psi) \Omega_t(\psi) \tag{37}$$

where

$$\Omega_t(\psi) = \sum_{i \in \psi} \frac{s_{it}}{s_t(\psi)} \omega_{it} = \sum_{i \in \psi)} s_{it}(\psi) \omega_{it} \tag{38}$$

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:

$$s_{it}(\psi) = \frac{s_{it}}{s_t(\psi)} \tag{39}$$

After having transformed the aggregate productivity expression into (37), 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 (37) gives us:

$$\Omega_t = \bar{\Omega}_t(\psi) + \sum_{\psi} (s_t(\psi) - 0.5)(\Omega_t(\psi) - \bar{\Omega}_t(\psi)) \tag{40}$$

$$= \bar{\Omega}_t(\psi) + \Gamma_t^B \tag{41}$$

D.3 Within type decompositions

Starting from equation (41) 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:

$$\begin{aligned} \bar{\Omega}_t(\psi) &= \frac{1}{2} \sum_{\psi} (\Omega_t(\psi)) \\ &= \frac{1}{2} \sum_{\psi} (\bar{\omega}_t(\psi) + \sum_{i \in \psi} (s_{it}(\psi) - \bar{s}_t(\psi))(\omega_{it} - \bar{\omega}_t(\psi))) \\ &= \frac{1}{2} \sum_{\psi} (\bar{\omega}_t(\psi) + \Gamma_t^{OP}(\psi)) \end{aligned} \tag{42}$$

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

D.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:

$$\Omega_t = \frac{1}{2}\sum_{\psi}\left[\bar{\omega}_t(\psi) + \Gamma_t^{OP}(\psi)\right] + \Gamma_t^{B}(\psi) \tag{43}$$

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.

E Measuring Productivity and Markups

We briefly discuss how we estimate productivity and recover markups using our plant-level panel on production and prices. This discussion will follow the exposition of control function estimation of productivity in Ackerberg, Frazer, and Caves (2006).

E.1 Productivity

We take equation (4) to the data and we follow the standard in the literature and rely on a plant's optimal investment equation to control for unobserved productivity shocks. Anticipating our markup analysis we specifically allow for intermediate inputs to be a variable input facing no adjustment costs, and include all relevant input demand variables such as wages, a firm's export status, in addition to their capital, labor and material use.[53]

Specifically, the first-stage of this procedure runs output r_{it} on a flexible function of inputs (l_{it}, m_{it}, k_{it}), an investment control function i_{it}, as well as year-plant type controls. In other words:

$$r_{it} = \phi_{\psi,t}(l_{it}, m_{it}, k_{it}, i_{it}) + \epsilon_{it} \tag{44}$$

And productivity is recovered as $\omega_{it} = \hat{\phi}_{it} - f_{\psi,t}(L_{it}, M_{it}, K_{it}; \boldsymbol{\beta})$. A key component into the estimation routine is the law of motion on productivity. In our baseline results we stick to an exogenous Markov process given by

$$\omega_{it} = g_{\psi}(\omega_{it-1}, \hat{\chi}_{it}) + \xi_{it} \tag{45}$$

Note that this evolution is allowed to vary for minimills and vertically integrated plants, as we have seen in the OLS regressions that vertically integrated plants slowly catch up to minimills. Moreover, we control for the selection effect due to the fact that we only observed productivity conditionally on a plant remaining in the industry using the estimated propensity score of exiting $\hat{\chi}_{it}$. To the extent that vertically integrated plant are larger and thus at an ex-ante level more likely to

[53] See De Loecker and Warzynski (2012) for more details

remain in the industry, this will generate differential selection rules for minimills and vertically integrated plants.

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 (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}.

The exact moments will depend on the functional form we select for $f(.)$. For our main specifications we rely on Cobb-Douglas production functions and use the following moments:

$$E\left(\xi_{it}(\boldsymbol{\beta})\begin{pmatrix} l_{it} \\ m_{it-1} \\ k_{it} \end{pmatrix}\right) = 0 \tag{46}$$

As a recent literature (Ackerberg, Frazer, and Caves, 2006) has pointed out that the identification of the variable input, the coefficient of β_m in our case, relies on sufficient variation in plant-level input prices which are serially correlated over time.[54]

E.2 Estimating Markups

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:

$$\mathcal{L}(V_{it}^1, ..., V_{it}^V, \mathbf{K}_{it}, \lambda_{it}) = \sum_{v=1}^{V} P_{it}^v V_{it}^v + \mathbf{r}_{it}\mathbf{K}_{it} + \lambda_{it}(Q_{it} - Q_{it}(V_{it}^1, ..., V_{it}^V, \mathbf{K}_{it}, \omega_{it})) \tag{47}$$

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

$$\frac{\partial \mathcal{L}_{ft}}{\partial V_{it}^v} = P_{it}^v - \lambda_{it}\frac{\partial Q_{it}(.)}{\partial V_{it}^v} = 0 \tag{48}$$

[54] All our results will be 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.

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.

$$\frac{\partial Q_{it}(.)}{\partial V_{it}^v} \frac{V_{it}^v}{Q_{it}} = \frac{1}{\lambda_{it}} \frac{P_{it}^v V_{it}^v}{Q_{it}} \tag{49}$$

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:

$$\mu_{it} = \theta_{it}^v (\alpha_{it}^v)^{-1} \tag{50}$$

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 $\theta_{it}^v = \beta_m$.