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

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A Data Appendix

A.1 Sample Selection

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

A.3 Coding Products

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

B Additional Tables and Figures

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

Vertically Integrated

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

Minimills

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

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

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

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

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

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

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

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

Table B.3: Production by Product

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

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

Table B.5: Exit and Profits

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

Note: Marginal Effects from a Probit presented.

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

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

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

Table B.7: Industry Productivity and Foreign Competition

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

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

Table B.8: Unionization Rates

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

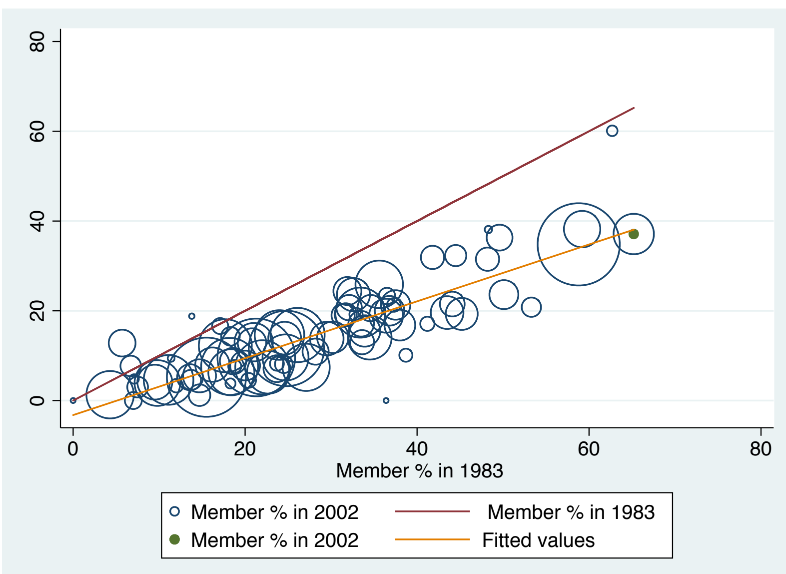
Note: The data are directly from the CPS database and was downloaded from `www.unionstats.com`.

Table B.9: Welfare effects under various demand elasticities

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

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

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



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

C Output and Input Deflators

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

C.1 Output price deflator

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

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

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

We start out with the following production function:

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

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

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

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

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

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

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

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

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

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

or in logs:

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

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

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

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

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

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

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

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

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

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

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

C.2 Input price deflator

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

C.2.1 Labor and capital

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

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

C.2.2 Intermediate inputs

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

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

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

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

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

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

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

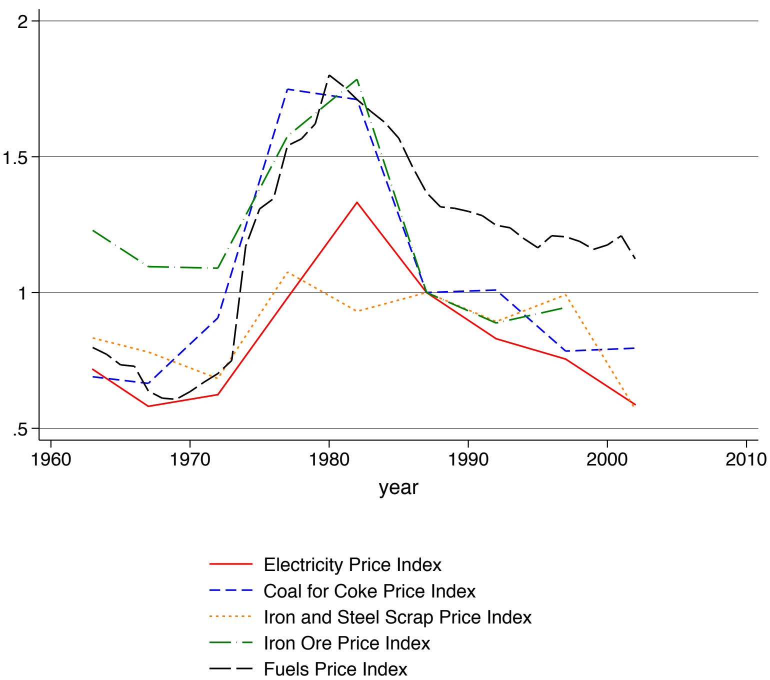
Table C.1: Intermediate Input use across Technology

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

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

Figure C.1: Price Trends for Inputs

Panel A: Material Inputs



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

Panel B: Labor Inputs

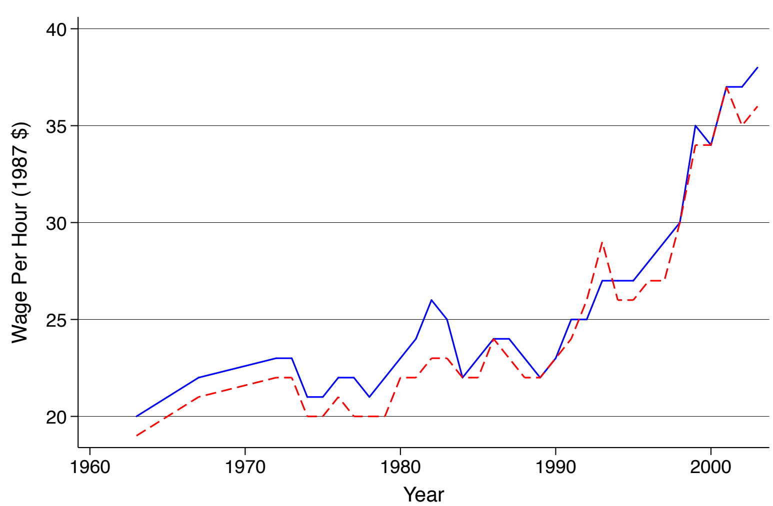


Table C.2: Input Shares: Materials

Panel A: Minimills Input Cost Share of Materials

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

Panel B: Vertically Integrated Input Cost Share of Materials

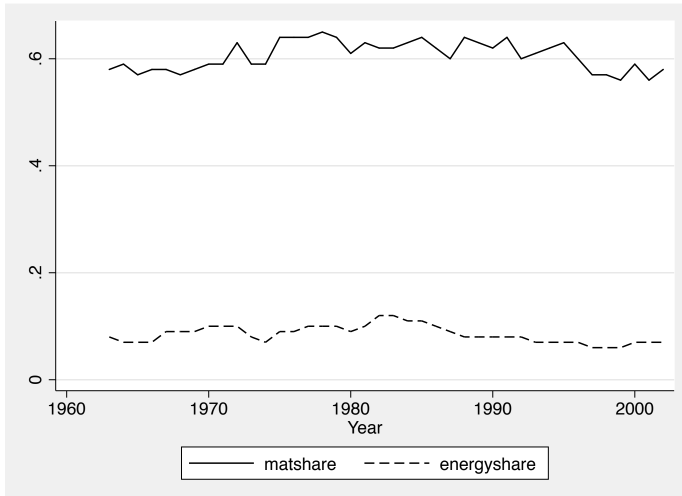
Year	Coal for Coke	Scrap	Iron Ore	Electricity	Fuels	Other
1963	.10	.08	.19	.02	.08	.52
1967	.10	.05	.16	.02	.06	.60
1972	.12	.05	.16	.03	.07	.57
1977	.17	.06	.13	.04	.14	.47
1982	.14	.07	.13	.06	.14	.46
1987	.12	.12	.12	.06	.08	.50
1992	.11	.08	.18	.06	.09	.47
1997	.09	.09	.19	.05	.09	.49
2002	.08	.11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

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

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

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

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



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

D Production function and markups: theory and estimation

D.1 Including labor as a state

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

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

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

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

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

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

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

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

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

The selection rule can be rewritten as:

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

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

We consider the following productivity process:

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

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

We rely on the following moments:

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

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

D.2 Recovering markups

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

The associated Lagrangian function is:

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

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

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

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

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

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

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

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

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

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

D.3 Technology-specific production functions

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

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

D.3.1 Conceptual framework

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

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

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

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

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

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

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

D.3.2 Disaggregation

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

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

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

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

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

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

E Deriving decompositions

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

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

where we define:

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

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

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

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

E.1 Standard OP

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

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

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

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

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

E.2 Deriving the Between covariance

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

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

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

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

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

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

where

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

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

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

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

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

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

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

E.3 Within type decompositions

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

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

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

E.4 Total decomposition

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

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

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

F Product reallocation

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

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

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

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

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