Innovation Subsidies: Misallocation and Technology Upgrade*

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Abstract

This paper examines TFP effects of size-dependent subsidies that generate misallocation but also incentivize technology adoption at the establishment-level in the context of a model with heterogeneous establishments and endogenous technology adoption. I focus on the subsidy program initiated in 2005 in Indian Iron and Steel industry which was directed to larger plants. Using plant-level data, I found that there was an acceleration of TFP growth but only among plants that used more productive technologies. Instead, I observed a larger reallocation across plants with less productive technologies after the policy change. I used a variant of the Lucas (1978) span-of-control framework with heterogeneous plants and endogenous technology choice at the establishment-level to explore if the subsidy policy contributed to the observed productivity growth. My findings indicate that size-dependent subsidies can increase aggregate TFP if the policy encourages technology adoption at the establishment-level. My calibrated model predicts that the subsidy program in India's Iron and Steel sector accounted for 1/5 of the observed aggregate TFP growth through three direct channels: First, the subsidy introduces idiosyncracy in the prices faced by individual plants causing resource misallocation (misallocation effect: -2%), Second, the subsidized plants with standard technology switch to the more efficient technology (technology upgrade effect: 49%), and finally, plants make new decisions on occupation and technology use (selection effect: 53%).

JEL Classification: L6, L11, O3, O4
Keywords: establishment-level productivity, TFP growth, size-dependent subsidy, resource misallocation, technology change, span-of-control

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1 Introduction

It is well understood that total factor productivity (TFP) plays a major role in understanding the differences in income levels between rich and poor countries, as well as in accounting for growth miracles and growth disasters within countries. An important follow-up question is, what are the proximate sources of low or high aggregate TFP? Broadly speaking, macroeconomists have emphasized two types of explanation in accounting for aggregate TFP, both across countries and within individual countries over time: (a) how productivity is determined at the plant-level (e.g., Aghion and Howitt, 1992; Parente and Prescott (1994, 1999, 2000); Schmitz (2005), and (b) how aggregate resources are allocated across plants of a given productivity (e.g., Restuccia and Rogerson, 2008; Hsieh and Klenow, 2009). At a deeper level, I would like to understand what particular policies and frictions lead to changes in productivity at the plant-level or cause misallocation.

In recent years, there has been substantial progress in measuring the extent of misallocation and quantifying its impact on aggregate TFP, as well as in assessing the quantitative importance of specific factors leading to misallocation (see Restuccia and Rogerson, 2013 for an excellent survey of this literature). However, only a few studies exist on policies that cause misallocation but also induce changes in productivity at the plant-level. In this paper, I ask what are the aggregate TFP effects of a subsidy policy that generates misallocation across plants while at the same time induces certain plants to adopt more productive technologies? Answering this question requires the use of establishment-level data in an environment in which the policy change is directly observed. I focus on a particular policy in a specific industry, in which the link between observed policy and productivity outcomes is tight. I use plant-level data from the Annual Survey of Industries (ASI) to study the aggregate TFP effects of a subsidy program in India's Iron and Steel sector.

India's remarkable growth over the last decade has made it one of the fastest growing economies in the world and an interesting subject of study. In addition, India has experienced major economic reforms since 1991, which could potentially have had significant impact on its manufacturing sector. One such reform was the National Steel Policy initiated by the Indian government in 2005 with the aim of capacity expansion and efficiency improvement in the Iron and Steel sector. An important component of the National Steel Policy was the subsidy program, which provided financial support for technology change, input upgrade and energy efficiency improvement. In practice, the policy was size-dependent in nature as the subsidies were given mainly to large producers.

For a first pass, I used the ASI plant-level data for growth accounting in Indian Iron and Steel sector. I used the index number approach developed by Petrin and Levinsohn (2005) to calculate aggregate industry TFP before and after the policy change in 2005. Then, I decomposed the TFP growth rate into a within-plant efficiency component and a reallocation component. My results show an acceleration of productivity growth following the 2005 reform: the growth rate of the aggregate TFP more than doubled, increasing from 1.72% over 1999-04 (before the reform) to 3.61% over 2005-2008 (after the reform). TFP decomposition also reveals that despite an increase in the share of reallocation growth from 4.7% in 1999-2004 to 14% in 2005-2008, the largest chunk of the aggregate TFP growth is attributed to the within-plant efficiency component rather than reallocation. In particular, within-plant efficiency growth contributed about 95% to the aggregate TFP growth in the industry before the policy change and 86% after the policy change.

What are the proximate sources of TFP growth in the Indian Iron and Steel sector? If within-plant efficiency growth is the main contributor to the aggregate TFP growth in the industry, then, technology improvement at the establishment-level would be a natural candidate to consider. The technologies operated by production units in Indian Iron and Steel sector can be grouped roughly into two categories: the "standard technology" which uses coal as the main fuel input, and the "efficient technology" which uses fuels other than coal (e.g. gas and electricity). It is widely acknowledged that the standard technology is less productive (less fuel-efficient) than the efficient technology (Hajim, 2009).[1] Unfortunately, the ASI does not provide information about which production technology is operated at the establishment-level. In order to get around this limitation of the data, I exploited the information reported by plants on their fuel expenditures to infer which technology was used by each plant. I calculated the share of each primary input in total fuel expenditure. If a plant used coal as a primary input and its cost accounted for at least 90% of the total fuel expenditure in that plant, I classified the plant as a standard producer. If the plan used one of the other primary inputs (gas, electricity of hydrocarbons), I classified it as an efficient plant. Using this mapping, I assigned plants to the two broad technology categories. Then, I repeated the growth accounting by calculating

[1]See also the Technology Roadmap Research Program for the Steel Industry published by the American Iron and Steel Institute in 2010 and available at www.steel.org.

changes in the TFP and its components (within-plant vs. reallocation) for units in each of the two technology categories.

The technology-wise growth decomposition shows that the within-plant productivity growth is accounted for mainly by plants operating fuel-efficient technologies (efficient producers) as opposed to coal-based, high-energy intensive technologies (standard producers). In addition, the reallocation induced TFP growth in the second period is accounted for by the initially coal-based plants. The share of the reallocation growth within the TFP growth of the standard producers increased from 8.9% in 1999-04 to 33.9% in 2005-08.

Next, I asked whether the 2005 subsidy program was an important underlying contributor to the aggregate TFP changes in India's Iron and Steel Industry, and if it was, through what channels did it manifest itself. In order to assess quantitatively how important the reform was in generating the industry TFP growth, I developed a simple general equilibrium model of firm heterogeneity with the possibility of technology upgrade at the establishment-level. In particular, I extended the Lucas (1978) span-of-control model to include a technology choice at the establishment-level along the lines of Adamopoulos and Restuccia (2012). In this model, individuals draw their managerial ability from an invariant and known distribution, and choose whether to become entrepreneurs and operate plants or become employees working at the plants. When setting up an establishment, each entrepreneur has access to two technologies: a "standard" technology and an "efficient" technology. The efficient technology has higher TFP but requires a higher fixed cost of operation relative to the standard technology. Aggregate TFP is determined by the allocation of individuals across occupations (hired workers vs. entrepreneurs), the allocation of resources across establishments, and the technology selection of entrepreneurs. In the absence of any distortions, individuals will optimally sort themselves across occupations and technologies, with the highest ability individuals operating efficient technology plants, intermediate ability individuals operating standard technology plants, and low ability individuals working as employees at both types of plants. The equilibrium is characterized by two cut-off levels of ability, where the lowest determines who becomes a worker vs. entrepreneur (occupational choice) and the second determines who operates the standard vs. efficient technology (technology choice). In other words, for a given distribution of managerial ability, the undistorted equilibrium implies an efficient distribution of plant sizes and technology usage. The efficient distribution of plant sizes and technologies can be observed from the ASI data which shows that the average number of workers in the efficient plants is always larger than the average employment size of standard plants.

Introducing a non-uniform subsidy policy in this framework with endogenous technology choice will generate three direct effects. First, holding fixed the number of plants operating each technology, the subsidy introduces idiosyncracy in the prices faced by individual producers, causing a reallocation of resources from non-subsidized to subsidized plant (misallocation effect). Second, the plants that receive the subsidies are motivated to switch to the efficient technology (technology upgrade effect). While the misallocation effect would tend to reduce aggregate industry TFP, the technology upgrade effect would tend to raise it. In addition, through general equilibrium effects, those who becomes workers and entrepreneurs, and what technology each entrepreneur chooses also impacts the aggregate industry TFP (selection effect). More specifically, the threshold for occupational choice increases and the threshold for technology choice decreases in response to the subsidy policy. Which effect dominates is a quantitative question.

To quantify the effects of the subsidy policy, I calibrated the model to India's Iron and Steel industry prior to the policy change in 2005. Then, I feed-in the policy, with the subsidy given being proportional to output. I assumed that the subsidies were financed through a lump-sum tax on consumers. I chose the subsidy rates to match the government spending as a percentage of annual turnover of Iron and Steel producers in India. In the calibrated model, the size-dependent nature of the subsidies is captured by allowing only plants with labor input above an exogenously set level to receive the subsidies. In the Indian Iron and Steel sector, large plants with multi-unit production facilities were the main participants in the subsidy program. In line with this, I set the exogenous employment cut-off for the subsidized plants to the minimum employment size of multi-unit plants before the policy change.

The misallocation effect can be captured in the above framework if the technology choice of entrepreneurs is shutdown. If all plants use a same technology, the size-dependent subsidies distorts only the occupation decisions of individuals, implying a misallocation of resources across/between large and small production units (level-effect). In this environment, the model predicts that the size-dependent subsidies lead to a small decrease in the aggregate TFP.

However, when plants are given a choice to select the technology, the size-dependent subsidies distort both the occupation decision of individuals and technology choice of entrepreneurs. The misallocation effect still generates aggregate TFP loss, however, the policy induces technology upgrading at the plant-level which increases the marginal benefit of production and does so more for the high TFP/efficient technology producers than it does for the low TFP/standard producers. As a result, marginal plants that are used to operating with the standard technology upgrade to the efficient technology. The positive impact of the technology upgrading is high enough to increase the aggregate industry TFP. The calibrated model with technology choice predicts that the size-dependent subsidies increase the industry TFP growth rate by 0.63%-0.71% which explains about 16%-21% of the aggregate TFP growth observed from data. The model also does well in predicting the gap in TFP growth rates of standard and efficient producers: the policy accounts for 44%-56% of the gap in TFP growth rates of plants with different technology. The source of the change in the industry TFP growth rate is attributed to a misallocation effect (-2%), technology upgrade effect (49%), and selection effect (53%).

2 Literature Review

The existence of large and persistent per capita income differences across rich and poor countries has attracted many theoretical and empirical studies. In the last two decades, establishment-level data has become available and economists have increasingly used it to better understand the sources of productivity gaps across/within countries. The focus of the emerging literature with the use of micro-level data has been to explain economic performance at the aggregate level by looking at heterogeneity at the establishment-level.

Among many factors at establishment-level that might be important in accounting for the dispersion of aggregate TFPs, two factors are most prominent. A country might be less productive because firms in that country use less productive technologies. Or, firms may have the frontier technologies, but without sufficient knowledge and skills, they are unable to incorporate the technologies efficiently. In this respect, the difference in the use of technology at the establishment-level is the source of low TFP at aggregate-level (Aghion and Howitt, 1992; Parente and Prescott, 1994).

In recent years, there is another view that aggregate TFP not only depends on the TFP of individual establishments, but also on how resources are allocated across them. The optimal resource allocation requires equalization of marginal products at the establishment-level. Idiosyncratic distortions can change relative prices faced by individual firms and alter the equalization of marginal returns of factors of production at the establishment-level. This deviation leads to a sub-optimal resource allocation (or the so-called misallocation) which ultimately reduces the levels of output and aggregate productivity.

There are many underlying factors which are thought to be important causes of misallocation. For example, the cost of firing employees in large establishments, favorable loans to local firms, the political connections of state-owned corporations, financial frictions such as the extra borrowing costs for small firms, and size-dependent taxes or subsidies – all can potentially lead to misallocation.

Restuccia and Rogerson (2013) conducted an excellent survey on misallocation and identified two types of empirical studies. The first set of empirical studies tries to understand the underlying factors that cause misallocation by considering one or more particular policies or institutions to examine the channel through which misallocation is generated, and then by quantifying the overall impact of misallocation on aggregate outcomes and firm performance. A study by Guner et al. (2008) considers policies that affect the size of establishments with a focus on the regulations in the retail sectors of Japan and France, employment protection in Italy, and subsidies for small and medium size enterprises in Korea. Their study indicates that policies that reduce the average size of establishments by 20% lead to reductions in output and output per establishment up to 8.1% and 25.6% respectively, as well as a large increase in the number of establishments (23.5%).

Adamopoulos and Restuccia (2011) looked at the 1988 Comprehensive Agrarian Reform Program (CARP) in the Philippines, that caped farm size at a legislated ceiling and the 1976 Amendment to the West Pakistan Land Revenue Act which imposed a progressive tax on farm sizes. Their quantitative assessment reports that the land reform in the Philippines reduced average size and agricultural productivity by 7%, while the tax reform in Pakistan reduced size and productivity by 3%.

In a study on capital market imperfection, Gilchrist et al. (2012) measures the extent of misallocation through borrowing costs of firms in a sub-set of the U.S. manufacturing sector from interest rate spreads on their outstanding publicly-traded debt. Their findings show that the resource loss due to the financial market frictions leads to relatively a small TFP decline of 1.5% to 3.5%.

Given the wide array of policies and institutions that can generate misallocation, another set of papers focus on "wedges" rather than specific policies and institutions. In this case, the overall effect of misallocation is the object of interest. Within this literature the well-known paper by Hsieh and Klenow (2009) shows that resource misallocation has led to sizable gaps in marginal products of labor and capital across plants within narrowly-defined industries in China and India compared to the U.S. Their quantitative results report that moving to the U.S. efficiency increases TFP in China by 30-50% and TFP in India by 40-60%. Restuccia and Rogerson (2008) also examine policies that create heterogeneity in the prices faced by individual firms and then measure the potential extent of output loss due to misallocation. They find that such policies can result to 30% decreases in output and aggregate TFP.

Bello, et al. (2011) study the link between misallocation and the growth collapse in Venezuela after the late 1950s. Their study points out many policies and institutions that misallocated resources to unproductive establishments, and shows that misallocation can explain most of the decrease in TFP and capital accumulation observed in Venezuela relative to the United States during the collapse period.

While in many studies, the impact of misallocation on aggregate output and TFP is measured holding establishment-level productivity fixed, a recent study by Gabler and Poschke (2013) evaluates distortions that not only generate misallocation but also impact the distribution of firm-level productivity. According to their framework, in the absence of distortions, firms engage in costly experiments that can promote their productivity level. However, if high productivity firms are subject to distortions (tax), firms have no incentive to invest in productivity increasing activities. In this case, the overall impact of misallocation on aggregate productivity is larger because the distortions not only misallocate resources across firms but also discourage firm from investing in activities that could lead to an increase in the level of productivity.

In this paper, I measure the quantitative impact of a policy that even though generates misallocation, it incentivizes technology upgrading at the establishment level. In particular, I consider the misallocation generated from the subsidy program in the Iron and Steel sector in India in 2005. In this sector, the subsidy program was the main source of financial support for innovation activities focused on the improvement of existing technologies, energy efficiency, and input upgrading. While in principle the allocation of subsidies was open to all firms, in practice the subsidies were effectively size-dependent, as they were only given to large Iron and Steel producers. The non-uniform distribution of subsidies creates heterogeneity in idiosyncratic prices faced by individual producers and led to misallocation. In contrast to the study of Gabler and Poschke (2013), in which distortions discourage productivity improvements at the establishment-level, the subsidy program in Indian Iron and Steel sector provided incentives for technology upgrade activities at the establishment-level. [2]

The rest of paper is organized as follows. In section 2, I describe India's Iron and Steel Industry and the National Steel Policy in more details. Section 3 shows the growth accounting and decomposition methodology and calculations using plant-level data. Section 4 describes the data, Section 5 describes the model. Section 6 explains the quantitative analysis and calibration. Section 7 concludes.

3 Indian Iron and Steel Industry and National Steel Policy

The Iron and Steel sector plays a crucial role in the Indian economy and contributes to about 2% of Gross Domestic Product (GDP) in India. The industry consists of primary (integrated) and secondary producers. The primary producers are large firms with multiple production units that handle several production stages, from the extraction of iron ore to the production of iron and steel. The complexity of the production process in the integrated units requires the use of advanced technologies that are heavily dependent on energy inputs. In contrast, the secondary producers are smaller firms with less complicated technologies that produce relatively simple products from low-priced materials.

Earlier development of India's Iron and Steel industry was subject to government control. In 1991, the industry experienced a major liberalization. The principal reforms included removing barriers on capacity, licensing, foreign investment, pricing, and trade. In 2005, the government introduced the National Steel Policy (NSP) to speed up the development of the Iron and Steel sector. The policy initiated a broad road-map to deal with inefficiency and focused on the expansion of capacity, along with mergers and acquisitions, input upgrading, energy efficiency

[2]The literature has stressed several reasons for why small firms participate less frequently in support programs than large firms. The level of firms' participation in a subsidy program is determined by the government decision to distribute the funds and implicitly, by the firm's decision to apply for the funds. For example, Heijs and Herrera (2004) discuss that small firms suffer from limitations of human resource and they often do not have enough time to prepare application forms or to gather information about various kinds of financial aids from the public administration. A prime empirical example is the study by Hanel (2003) on the effect of innovation support programs by the Canadian government on manufacturing firms. Hanel shows that small firms participated in the R&D less frequently than large firms. In addition, a limited capacity of innovation management in small firms could have delayed the conversion of their innovation activities into well-organized projects with clear objectives which is necessary to apply for the funds.

improvement and technology change. The long-term goal of the National Steel Policy is to attain production of over 100 million tonnes per year by 2020 (from 38 million tonnes in 2005 implying a compounded annual production growth rate of 7.3 percent). [3]

In terms of innovation and technological change, the Iron and Steel companies in India have a relatively smaller investment in R&D compared to the top steel producers in the world. For instance, China, as the world largest steel producer, invests in R&D more than all the investment made by rest of the world combined. To spur technological progress, the draft NSP initiated sustained budgetary support of of various innovation and technology improvement activities in the industry. [4] According to information provided by India's Ministry of Steel, since 2005, the government has allocated around 20 to 40 million dollars per year to finance well-defined projects in various areas such as input upgradings, reduction in energy consumption, and technology progress. In addition to these direct funds, the ministry organized particular sessions and constituted a "Task Force" to review the existing institutional infrastructure available for research and development in steel producers. The task force was to determine the existing shortages and set up an advanced R&D center to utilize domestically available resources. For example, under this program, firms could receive a one-time grant of 10 million dollars during the first three years and the full establishment cost of a virtual center for R&D activities. In addition, the government approved a new scheme called the "Scheme for Promotion of R&D in Iron & Steel Sector" for which an additional amount of 25 million dollar has been allocated for the period of 2007-12.

The Indian government also promoted capacity expansion projects in the industry through the support of large-capacity technologies and mergers and acquisitions initiatives. For example, since 2005, many integrated producers have signed memoranda of understanding (MoUs) with different states for planned capacity (mainly in the states of Orissa, Jharkhand, Chattisgarh, West Bengal, Karnataka, Gujarat and Maharashtra). The industry had already experienced 20 million tonnes of expansion in the finished steel manufacturing capacity during 2005-10. [5]

[3]Crude steel production in India grew at 8% annually from 46.46 million tonnes in 2006 to 69.57 million tonnes in 2011.

[4]According to the World Steel Association, efficiency improvements could lead to reductions of up to 50 percent of energy required to produce a tonne of crude steel.

[5]Reference: India's Ministry of Steel Annual Report.

4 Growth Accounting and Productivity Decomposition

India's manufacturing sector has been the subject of research in many empirical studies. A recent paper on growth accounting in the Indian manufacturing sector is the study by Bollard, Klenow, and Sharma (2013). Using micro-level data, their study measured the aggregate manufacturing TFP and presents evidence of a substantial speedup in manufacturing TFP growth in India. Their estimate of the TFP growth rate was over 5 percentage points per year for 1993-2007 vs. 1980-1992. They looked for the source of the aggregate manufacturing TFP growth in India. However, the overall results of their analysis did not provide conclusive evidence on whether liberalization enhances productivity growth in the Indian manufacturing sector.

There are only a few studies available that estimate the total factor productivity in Indian Iron and Steel sector. The results are not conclusive and range from suggesting there had been an improvement to reporting a decline in the sector's productivity level. A study by Schumacher and Sathaye (1998) using industry-level data reports that the total factor productivity in India's Iron and Steel industry shows a downward trend of 1.71% per year from 1973-74 to 1993-94. They found that the decline was mainly because of price protective policies and the inefficiency of major public steel plants. In another study, Ray and Pal () used industry-level data and conducted a productivity comparison of before and after liberalization in the period of 1980-92 and 1992-04. Their study shows evidence of improvement in partial productivity measures (labor and capital) after liberalization (1992-2004) but the results of overall productivity performance show declining TFP growth. They found that the significant output growth in India's Iron and Steel industry was mainly input-driven rather than productivity-driven and that resource misallocation is the major obstacle to productivity growth.

In the next section, I calculate the industry TFP and its component for the period of 1999 to 2008. First, I explain the methodology that I use for growth accounting and TFP decomposition using plant-level data.

Framework

Following Basu and Fernald (2002) and Petrin and Levinsohn (2005), I used an index number approach to calculate TFP growth rates and then I decomposed it into a within-plant efficiency component and a reallocation component over 1999-2008, as well as both before and after the policy change in 2005. The index number approach is a straightforward method of calculating

TFP and its components without any estimation (Biesebroeck, 2007). The main advantage of the index number approach is that it enables researchers to handle multiple outputs and inputs cases while flexible and heterogeneous production technology is allowed.

To start, consider the following production technology used by plant i at time t:

$$Q_{it} = H(A_{it}, X_{ijt}, E_{iet}, P_{et}, P_{xt})$$

I denoted Q_{it} as the maximum quantity of gross output that can be produced by plant i at time t using primary and intermediate inputs. Primary inputs X indexed by j include skilled labor l_s, unskilled labor l_u, and capital k. Intermediate inputs E indexed by e include basic materials m and fuel f. I denoted the price of primary and intermediate inputs by P_e and P_x. The value-added function Y_{it} represents the maximum amount of current-price value-added that is produced by plant i, given a set of primary inputs, and its shadow prices P_x. For simplicity, the price of output was normalized to one.

$$Y_{it} = F(A_{it}, X_{ijt}, P_{xt}) \tag{1}$$

The aggregate TFP growth in the industry based on value-added is defined as,

$$da_t = dy_t - dx_t \tag{2}$$

where dy_t and dx_t are aggregate growth rates of value-added output and primary inputs. The aggregate TFP growth can be decomposed into a within-plant efficiency growth component and a reallocation growth component.

$$da_t = \frac{1}{Y_t}\sum_i Y_{it} da_{it} + \frac{1}{P_{xt}X_t}\sum_i \sum_j (P_{ijt} - P_{jt}) X_{ijt} dx_{ijt} \tag{3}$$

where Y_{it} denotes the nominal value-added of plaint i, da_{it} denotes plant level TFP, $P_{xt}X_t$ stands for total input expenditures, and X_{ijt} represents the quantity of each primary input j used by plant i. The first term in this equation is the weighted average of within-plant efficiency growth and the second term reveals reallocation growth. Since the shadow input prices P_{ijt} are not observable, I calculate the aggregate TFP growth rate and within-plant efficiency growth rate first. The residual difference between the two terms gives the reallocation component.

To calculate within-plant efficiency growth, first, I approximated the plant-level productivity growth da_{it} from:

$$da_{it} = dy_{it} - \alpha_{it}^{lu}\, dl_{it}^{u} - \alpha_{it}^{ls}\, dl_{it}^{s} - \alpha_{it}^{k}\, dk_{it} \tag{4}$$

In this equation, dy_{it} denotes the plant value-added growth rate which is calculated from the Divisia value-added growth formula and the Törnqvist Index as follows.[6]

$$dy_{it} = \frac{dq_{it} - \beta_{it}^{m}\, dm_{it} - \beta_{it}^{f}\, df_{it}}{1 - \beta_{it}^{m} - \beta_{it}^{f}} \tag{5}$$

where, α_{it}^{j} is the share of primary input j in the output of a plant i at time t and is given by,

$$\alpha_{it}^{j} = \frac{\alpha_{it}^{j} + \alpha_{it-1}^{j}}{2}\ ,\ j \in \{l^u, l^s, k\}$$

and, β_{it}^{e} is share of intermediate input e in output of a plant i at time t, given by,

$$\beta_{it}^{e} = \frac{\beta_{it}^{e} + \beta_{it-1}^{e}}{2}\ ,\ e \in \{m, f\}$$

All the growth rates are calculated as difference in natural logarithms. For example, for unskilled labor, the dl_{it}^{u} is given by,

$$dl_{it}^{u} = ln(l_{it}^{u}) - ln(l_{it-1}^{u})$$

5 Data

The Annual Survey of Industries (ASI) is the main source of industrial statistics in India. The ASI provides a variety of information on the value of output, assets (capital), employment and wages, value and types of materials and fuels at plant level. The ASI sampling frame includes all registered factories employing 10 or more workers using power, or factories with 20 or more workers without power. Production units in the survey are coded based on the National Industrial Classification (NIC). To extract the Iron and Steel sector from ASI, I use the NIC 1998 and NIC 2004. Under both industrial classification codes, basic metal products are classified under division 27, and group 271 which represents Iron and Steel products. With

[6] The Törnqvist index is a discrete approximation to calculate growth rates. For a Törnqvist index, the growth rates are defined to be the difference in natural logarithms of successive observations of the plants. The weights are equal to the mean of the factor shares of the components in aggregate output.

this, I can construct a sample of 1200 production units on average per year representing Indian Iron and Steel sector. The details of Iron and Steel products under division 27 are provided in appendixes.

Table 1: Average Number of Plants Per Year in Total Sample

	1999-2004	2005-2008	1999-2008
Number of Plants	950	1590	1200

The set of manufacturing units covered in every survey is called the "census" while rest of the units, which are chosen randomly, are treated as the "sample". Census units for the period of 1999-04 include all manufacturing units with 200 employees or more, plus units with fewer than 200 employees but with significant contribution to the value of output, as well as all units in 12 industrially backward states. The definition of the census sample has been changed since 2005 and now covers units with 100 or more employees plus all the plants in the five industrial backward states (see Appendix for more information on ASI sampling design). To have a reliable panel, this study uses both "census" and "sample" units between 1999 and 2008. The final sample includes 60% of sample units and 40% of census units. Figure 2 also shows the share of census units in the final sample.

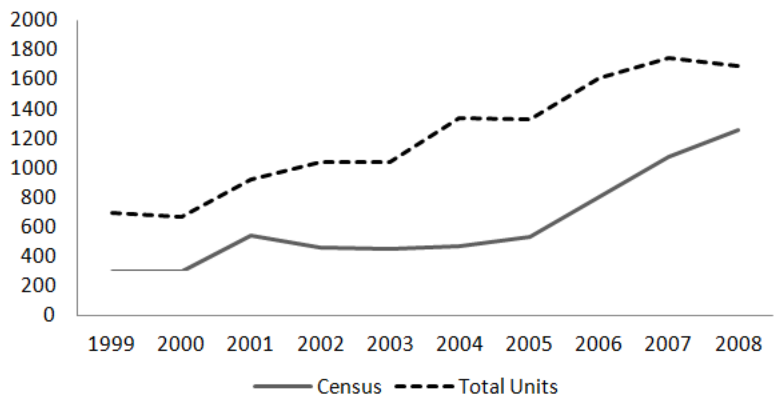

Figure 1: Number of Units in Census Sample vs. Total Sample

The growth accounting undertaken in this study requires observations on individual production units every two consecutive years (t and $t-1$). In the ASI prior to 2005, plants were not assigned a unique identification number, so, it is not possible to link up directly the plant observations for every two years. So, I used a matching procedure following Bollard, Klenow, and Sharma (2013) to link production units across every two years from 1999 to 2005. I used information on several identification variables which are reported on a consistent basis every year. These include the year of initial production, state code, district code, sector code, type of organization, and type of ownership. The initial year of production and state code remain unchanged over time. I matched plants based on the initial year of production first. Dropping unmatched observations, I linked plants with the second identification variable (state code). This procedure was continued for the rest of the identification variables. To minimize possible errors, I ensured that for the plants in the final sample, the closing value of fixed assets was close to the opening value of the next year. The final sample contains plants that were matched based on at least 3 identification variables. To reduce the effect of spurious outliers, observations with extreme values were dropped from the sample. By the matching procedure, between 40-60% of units are matched in average in every two consecutive years.

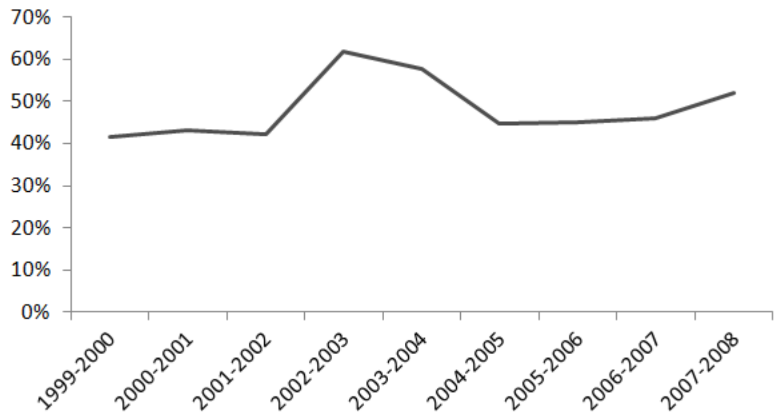

Figure 2: Percentage of Matched Plants to Previous Year Record

All the values in the data are deflated based on the price indexes provided by the Handbook of Statistics on Indian Economy published by the “Reserve Bank of India”. In particular, the value of output was deflated with a price index for “basic materials and alloy industries”. The material was deflated by the price index of intermediate goods, and each fuel (coal, gas, electricity and hydrocarbons) was deflated by its own price index.

TFP Growth Rates and Decomposition

Table 2 outlines the aggregate TFP growth rates and the share of reallocation growth in the growth rates. All the growth rates are reported as yearly average. The industry TFP grows averaged 1.72% over 1999-04, 3.61% over 2005-08 and 2.56% over the whole period of 1999-08. The within-plant efficiency was the main source of productivity gain in the industry both before and after the policy change and it accounts for over 95% of the aggregate TFP growth in 1999-04. However, reallocation plays a higher role (15% of the aggregate TFP growth) after the policy change.

Table 2: Aggregate TFP Growth Rates and Share of Reallocation (Average Annual)), %

Period	1999-04	2005-08	1999-08
Aggregate Productivity	1.72	3.61	2.56
Share of Reallocation	4.7	13.9	10.4

What was the underlying cause of within-plant efficiency growth in India's Iron and Steel industry? Given that the sector was highly technology-dependent, a natural candidate for the acceleration of within-plant efficiency growth is technological progress. In the ASI data, plants do not report the types of technology that they use in production, therefore, it is impossible to observe directly if there has been any change in technology use over time. However, Iron and Steel making processes are extremely intensive in material and energy usage. A wide range of Iron and Steel making technologies are characterized by the types of primary fuel input. Plant operators are forced to choose a technology that makes their production facilities energy-efficient. The answer to the question of which technology is appropriate lies in the cost and quality of fuel inputs as well as the capacity of the production unit. Knowing these requirements helps managers to decide, for instance, if a coal-based furnace should be used in production or an electric arc furnace. [7]

So, I used expenditures of primary fuel input as a proxy to infer the production technologies in the industry. Coal is a plentiful and cheap source of fuel in India and coal-based technologies are relatively less expensive but important to produce low-priced Iron and Steel products. Coal-based technologies are inefficient and outdated compared to alternative technologies that use an efficient fuel like gas, hydrocarbons, or electricity. [8] As a first pass, I calculated the share of

[7] Fuel in some technologies constitutes up to 50% of the total production cost.

[8] For detailed information about steel production technologies and their efficiencies, see the Technology

each primary fuel input in total fuel expenditures and classified the plants that use coal as a primary input as standard plants and plants that use other fuels (natural gas, hydrocarbons, or electricity) as efficient plants. With this technology split, the standard technology becomes the less productive technology (less fuel-efficient) than the efficient technology but less expensive too.

This classification may not represent the entire technological features of the industry, but it is consistent with the Iron and Steel making process in India. For example, in the iron-making step, iron ore is reduced to either pig iron (low quality iron) or sponge iron (high quality iron). Pig iron production occurs in Blast Furnaces (BF) where coal is the primary fuel (this is classified as standard technology). "Direct Reduced" is an alternative technology that produces sponge iron using fossil fuels (this is classified as the efficient technology). The conversion of ore into pig iron is more energy-intensive and less efficient than conversion of iron ore to sponge iron. The steel production step also involves two main technologies: Open Hearth Furnace (OHF) and Basic Oxygen Furnace (BOF). OHF is an old technology with high capital costs and fuel consumption. In an OHF process, over 90% of the fuel comes from coal, 3%-4% percent from gas and 1%-2% from liquid fuels (OHF is classified as the standard technology). In contrast, BOF is a newer technology with higher efficiency. The main energy input in BOF process is gas or combination of gas and other fuels (this is classified as the efficient technology). A typical technology change would be to switch from one technology to another. For example, in many steel producing units in India, Open Hearth Furnaces have been shutdown or replaced by the alternative technologies (e.g. Basic Oxygen Furnace) which leads to a decrease in the average share of crude steel production by OHF from 16.6% over 1990-04 to 2% over 2005-08.

Next, I recalculated the TFPs and their components for plants with standard and efficiency technologies. The following table shows the results. Plants with the efficient technology grew significantly faster during 2005-08 with an average growth rate of 5.33% per year compared to 1.89% in 1999-04. While, producers with the standard technology experience a decline in average productivity growth rate from 1.16% per year in the first period to -0.61% over 2005-08. For the both types of plants, within-firm efficiency remains as the main source of productivity growth. However, for the standard producers, the share of reallocation has increased from 8.9% in 1999-04 to 33.9% during 2005-08 indicating a large reallocation of inputs across standard

Roadmap Research Program for the Steel Industry published by American Iron and Steel Institute in 2010 and available at www.steel.org.

producers and between plants with different technologies.

Table 3: Aggregate Productivity Growth and Share of Reallocation (Average Annual), %

		1999-04	2005-08	1999-08
Standard Producers	Aggregate Productivity	1.16	-0.61	0.37
	Share of Reallocation	8.9	33.9	9.3
Efficient Producers	Aggregate Productivity	1.89	5.33	3.42
	Share of Reallocation	2.7	7.0	5.7

An important statistic that can be observed from the technology-wise growth accounting is the gap in the growth rates of plants with different technologies both before and after the policy change. While all the production units grew at slightly different rates before the policy change (1.16% vs. 1.89%), the acceleration of TFP growth of efficient plants along with declining TFP growth of standard plants, increased productivity growth gap between standard and efficient producers. This gap has increased from 0.73% in 1999-04 to 5.94% in 2005-08.

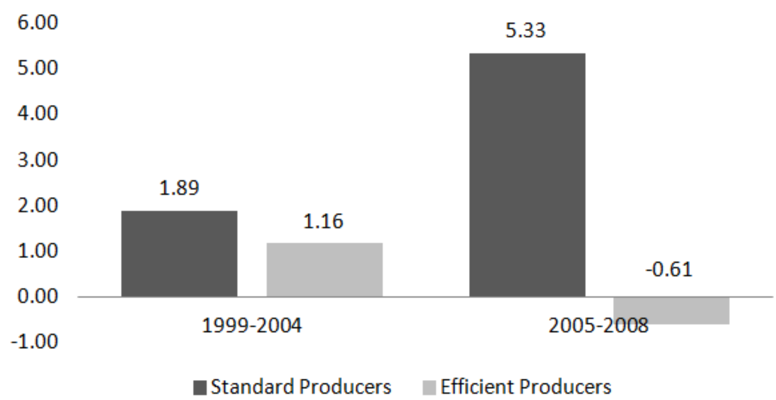

Figure 3: Gap in TFP Growth Rates of Standard and Efficient Plants

So far, our productivity growth accounting and technology split provide evidence of technological change in the Indian Iron and Steel industry after 2005. However, the results cannot provide conclusive evidence if the subsidy program was an important contributor to the changes in TFP growth rates. In the next section, I develop a quantitative framework to examine if the subsidy policy was quantitatively important in accounting for the changes in TFP growth and the gap between plants with different technologies.

6 A Model of Plant Size and Technology Choice

I considered a standard version of the Lucas (1978) span-of-control industry model. Each individual in the economy is endowed with a set of skills to become an entrepreneur. The skills can be considered as variety of someone's experience of different industries, companies, and technologies. The set of skills (or managerial talent) is fixed across time but varies across individuals. As in the standard span-of-control model, entrepreneurs tend to have more skills than employees. Occupation choice decision depends on an individual's level of skills and is determined by a comparison of benefits from being an entrepreneur (producer) versus a paid worker. Each individual that chooses to become entrepreneur will represent one production unit (plan) and in total they create an industry with heterogeneous producers. In this framework, the size of each establishment is endogenous and depends on the managerial ability of its entrepreneur.

To incorporate an endogenous technology change, I extend the Lucas span-of-control model to include a technology choice at the establishment-level along the lines of Adamopoulos and Restuccia (2012). When an individual decides to become an entrepreneur, he/she has access to two technologies, a "standard" technology and an "efficient" technology that are different in terms of TFP and fixed cost. In particular, the efficient technology is more productive but it requires a higher fixed cost relative to the standard technology. In this framework, the aggregate TFP is determined by the allocation of individuals across occupations, the allocation of resources across establishments, and the choice of technology use of entrepreneurs.

Without distortions, there is an optimal allocation of individuals across two occupations (working vs. entrepreneurship) and allocation of efficient and standard technology across plants. The equilibrium is characterized by two cut-off levels of ability, where the lowest determines who becomes a worker vs. entrepreneur (occupational choice) and the second determines who operates the standard vs. the efficient technology (technology choice).

To start, consider an industry that has a given quantity of homogenous capital K and a given labor-force L_a. The individual's level of skills s is drawn from an exogenous and time invariant distribution function represented by *cdf* $G(s)$ and *pdf* $g(s)$.

The initial allocation of resources involves a division of labor-force into workers L and the rest to entrepreneurs $L_a - L$. To operate, a plant with productivity level s must choose either the standard technology with productivity parameter κ_n and technology-specific cost c_n, or, the efficient technology with productivity parameter κ_m and technology-specific cost c_m while

$\kappa_m > \kappa_m$ and $c_m > c_n$. Then, it employs an efficient amount of capital $k(s)$, and labor $l(s)$ and produces output according to a decreasing return to scale technology given by,

$$y_i(s) = (\kappa_i s)^{1-\gamma} \, (k_i(s)^{\alpha} \, l_i(s)^{1-\alpha})^{\gamma}, \;\; i \in \{n, m\}, \;\; \kappa_m > \kappa_n \tag{6}$$

A plant with a given productivity s and technology i maximizes profit with a given market wage rate w and rental rate of capital r.

$$\pi_i(s) = max \, \{y_i - w \, l_i(s) - r \, k_i(s) - c_i\}$$

where c_i is the fixed cost of technology i and is measured in units of output. Plants are competitive in output and factor markets. Conditional on operating, the first order conditions give demands for labor and capital as,

$$k_i(s) = (\frac{\alpha}{r})^{\frac{1-(1-\alpha)\gamma}{1-\gamma}} \, (\frac{1-\alpha}{w})^{\frac{(1-\alpha)\gamma}{1-\gamma}} \, \gamma^{\frac{1}{1-\gamma}} \, \kappa_i \, s \tag{7}$$

$$l_i(s) = (\frac{\alpha}{r})^{\frac{\alpha\gamma}{1-\gamma}} \, (\frac{1-\alpha}{w})^{\frac{1-\alpha\gamma}{1-\gamma}} \, \gamma^{\frac{1}{1-\gamma}} \, \kappa_i \, s \tag{8}$$

All plants have the same capital-labor ratio which is independent of the plant productivity level s, and the technology-productivity parameter κ.

$$\frac{l}{k} = (\frac{1-\alpha}{\alpha}) \, (\frac{r}{w}) \tag{9}$$

Since the demands for labor and capital are linear in productivity parameter s, output and profit at plant level remain linear in s too. This implies that large establishments are operated by entrepreneurs with the higher level of managerial skills.

$$y_i(s) = (\frac{\alpha}{r})^{\frac{\alpha\gamma}{1-\gamma}} \, (\frac{1-\alpha}{w})^{\frac{(1-\alpha)\gamma}{1-\gamma}} \, \gamma^{\frac{\gamma}{1-\gamma}} \, \kappa_i \, s \tag{10}$$

$$\pi_i(s) = (1-\gamma) \, y_i(s) - c_i$$

Decisions

In a stationary environment, the efficient allocation of individuals between workers and entrepreneurs is determined by a comparison of the job market wage rate w and the profit earned under the standard production technology $\pi_n(s_n)$. The condition yields a threshold level of skills s_n at which, an individual becomes indifferent to whether they become a hired worker or an entrepreneur. This lower level of threshold is calculated,

$$\pi_n(s_n) = w \tag{11}$$

The second threshold of skills s_m is determined by a comparison of expected profits earned as a producer with the standard technology and a producer with the efficient technology.

$$\pi_n(s_n) = \pi_m(s_m) \tag{12}$$

Note that in equilibrium and in the absence of any distortions, individuals will optimally sort themselves across occupations and technologies. Individuals with the highest level of ability operate efficient technology plants, individuals with intermediate level of ability run the standard technology plants, and individuals with the lowest level of ability work as employees at the both types of plants. The undistorted equilibrium also implies an efficient distribution of plant sizes and technology usage.

Subsidy Policy and Industry TFP

Let us assume that the government introduces a subsidy policy and each plant is subject to a subsidy to output $\tau(s)$. Since the policy aims to promotes large units, only plants with number of workers above a threshold can receive the subsidies. I define $\bar{l}$ the cut-off employment threshold for subsidized plants. $\bar{l}$ is exogenous and is determined by the government. Producers with standard or efficient technology can receive the subsidies as long as their employment size is above $\bar{l}$. The subsidy rate remains fixed as long as the plant is in operation.

$$\tau(s) = 0, \quad \text{if } l_i \; < \; \bar{l}$$

The policy changes the profit maximization problem of subsidized plants and their demands for capital and labor. Given the wage rate w and the rental price of capital r, the profit maximization problem of a firm s with technology i changes to,

$$\pi_i(s) = max\{(1 + \tau(s))\, y_i - w\, l_i(s) - r\, k_i(s) - c_i\}$$

The distortions generated from the size-dependent subsidies alter plant-level decisions and impact optimal allocation of resources across plants as well the optimal technology selections. It can be shown that the lower threshold of skills becomes,

$$s_n = \frac{w + c_n}{(1+\tau(s)_n)^{\frac{1}{1-\gamma}}\,(1-\gamma)\,\kappa_n}(\frac{\alpha}{r})^{\frac{-\alpha\gamma}{1-\gamma}}\,(\frac{1-\alpha}{w})^{\frac{-(1-\alpha)\gamma}{1-\gamma}}\,\gamma^{\frac{-\gamma}{1-\gamma}} \tag{13}$$

where $\tau(s)_n$ is the subsidy rate to plants with productivity s and technology n. A lower wage rate or a higher subsidy rate increase expected profit of entrepreneurship and reduce the lower threshold of skills s_n. This motivates marginal workers with the highest level of ability to enter the industry and become entrepreneurs.

The upper threshold of skills also changes to,

$$s_m = \frac{c_m - c_n}{(1-\gamma)\,\Big((1+\tau(s)_m)^{\frac{1}{1-\gamma}}\,\kappa_m - (1+\tau(s)_n)^{\frac{1}{1-\gamma}}\,\kappa_n\Big)}(\frac{\alpha}{r})^{\frac{-\alpha\gamma}{1-\gamma}}\,(\frac{1-\alpha}{w})^{\frac{-(1-\alpha)\gamma}{1-\gamma}}\,\gamma^{\frac{-\gamma}{1-\gamma}} \tag{14}$$

where $\tau(s)_m$ denotes the subsidy rate faced by producers s and technology m.

Market Clearing Conditions

In equilibrium, there exist two types of establishments: high productivity entrepreneurs who operate larger plants using the efficient technology and entrepreneurs with lower level of productivity who run smaller plants using the standard technology. The aggregate demands for capital and labor are determined by wage rate w, rental rate of capital r and the productivity distribution condition on entry $g_c(s)$. Setting the maximum level of skills at s_{max}, the sum of the labor and capital employed by standard and efficient plants gives the aggregate labor and capital in the industry.

$$K = K_n + K_m = \sum_{s_n}^{s_m} k_n(s)\,g_c(s) + \sum_{s_m}^{s_{max}} k_m(s)\,g_c(s) \tag{15}$$

$$L = L_n + L_m = \sum_{s_n}^{s_m} l_n(s)\,g_c(s) + \sum_{s_m}^{s_{max}} l_m(s)\,g_c(s) \tag{16}$$

Aggregate industry output equals sum of outputs produced by plants with different technologies.

$$Y = Y_n + Y_m = \sum_{s_n}^{s_m} y_n(s)\, g_c(s) + \sum_{s_m}^{s_{max}} y_m(s)\, g_c(s) \tag{17}$$

To find an expression for the industry TFP and TFP of plants with standard and efficiency technologies, I aggregated capital and labor in equations (7) and (8) over technology i and calculated total capital and labor employed by each group of producers.

$$K_i = (\frac{\alpha}{r})^{\frac{1-(1-\alpha)\gamma}{1-\gamma}} (\frac{1-\alpha}{w})^{\frac{(1-\alpha)\gamma}{1-\gamma}} \gamma^{\frac{1}{1-\gamma}} \left(\kappa_i \sum_{s_i}^{s_{i+1}} s\,(1+\tau(s)_i)^{\frac{1}{1-\gamma}}\, g_c(s)\right) \tag{18}$$

$$L_i = (\frac{\alpha}{r})^{\frac{\alpha\gamma}{1-\gamma}} (\frac{1-\alpha}{w})^{\frac{1-\alpha\gamma}{1-\gamma}} \gamma^{\frac{1}{1-\gamma}} \left(\kappa_i \sum_{s_i}^{s_{i+1}} s\,(1+\tau(s)_i)^{\frac{1}{1-\gamma}}\, g_c(s)\right) \tag{19}$$

where s_i and s_{i+1} are the lower and upper productivity thresholds of establishments with technology i. $g_c(s)$ denotes the conditional productivity distribution. Combining (18) and (19) gives,

$$\left(K_i^{\alpha} L_i^{1-\alpha}\right)^{\gamma} = (\frac{\alpha}{r})^{\frac{\alpha\gamma}{1-\gamma}} (\frac{1-\alpha}{w})^{\frac{(1-\alpha)\gamma}{1-\gamma}} \gamma^{\frac{\gamma}{1-\gamma}} \left(\kappa_i \sum_{s_i}^{s_{i+1}} s\,(1+\tau(s)_i)^{\frac{1}{1-\gamma}}\, g_c(s)\right)^{\gamma} \tag{20}$$

Now, from (10), we can calculate the aggregate output of producers with technology i as,

$$Y_i = (\frac{\alpha}{r})^{\frac{\alpha\gamma}{1-\gamma}} (\frac{1-\alpha}{w})^{\frac{(1-\alpha)\gamma}{1-\gamma}} \gamma^{\frac{\gamma}{1-\gamma}} \left(\kappa_i \sum_{s_i}^{s_{i+1}} s\,(1+\tau(s)_i)^{\frac{\gamma}{1-\gamma}}\, g_c(s)\right) \tag{21}$$

substituting (20) in (21) yields,

$$Y_i = (TFP_i)^{1-\gamma} \left(K_i^{\alpha}\, L_i^{1-\alpha}\right)^{\gamma}$$

where, the aggregate TFP for producers with standard and efficient technologies is given by,

$$TFP_n = \kappa_n \frac{\left(\sum_{s_n}^{s_m} s\,(1+\tau(s)_n)^{\frac{\gamma}{1-\gamma}}\, g_c(s)\right)^{\frac{1}{1-\gamma}}}{\left(\sum_{s_n}^{s_m} s\,(1+\tau(s)_n)^{\frac{1}{1-\gamma}}\, g_c(s)\right)^{\frac{\gamma}{1-\gamma}}} \tag{22}$$

$$TFP_m = \kappa_m \frac{\left(\sum_{s_m}^{s_{max}} s\,(1+\tau(s)_m)^{\frac{\gamma}{1-\gamma}}\, g_c(s)\right)^{\frac{1}{1-\gamma}}}{\left(\sum_{s_m}^{s_{max}} s\,(1+\tau(s)_m)^{\frac{1}{1-\gamma}}\, g_c(s)\right)^{\frac{\gamma}{1-\gamma}}} \tag{23}$$

Note that, without subsidies, or, if the subsidies are given to all plants in the industry, the aggregate TFP of standard and efficient producers become independent of the subsidy rate and becomes the weighted average of the plant level productivity indexes s.

$$TFP_i^* = \kappa_i \sum_{s_i}^{s_{i+1}} s\, g_c(s)$$

Now, to find an expression for the aggregate industry TFP, I calculated the aggregate capital ($K = K_n + K_m$) and labor ($L = L_n + L_m$) for the whole industry first. It can be shown that,

$$\left(K^{\alpha} L^{1-\alpha}\right)^{\gamma} = \left(\frac{\alpha}{r}\right)^{\frac{\alpha\gamma}{1-\gamma}} \left(\frac{1-\alpha}{w}\right)^{\frac{(1-\alpha)\gamma}{1-\gamma}} \gamma^{\frac{\gamma}{1-\gamma}} \left[V_n + V_m\right]^{\gamma} \tag{24}$$

where V_i is defined as;

$$V_n = \kappa_n \sum_{s_n}^{s_m} s\,(1+\tau(s)_n)^{\frac{1}{1-\gamma}}\, g_c(s)$$

$$V_m = \kappa_m \sum_{s_m}^{s_{max}} s\,(1+\tau(s)_m)^{\frac{1}{1-\gamma}}\, g_c(s)$$

Then, I define the aggregate output of the industry as the sum of outputs produced under each technology ($Y_n + Y_m$),

$$Y = \left(\frac{\alpha}{r}\right)^{\frac{\alpha\gamma}{1-\gamma}} \left(\frac{1-\alpha}{w}\right)^{\frac{(1-\alpha)\gamma}{1-\gamma}} \gamma^{\frac{\gamma}{1-\gamma}} \left(W_n + W_m\right) \tag{25}$$

where W_i is defined as;

$$W_n = \kappa_n \sum_{s_n}^{s_m} s\,(1+\tau(s)_n)^{\frac{\gamma}{1-\gamma}}\, g_c(s)$$

$$W_m = \kappa_m \sum_{s_m}^{s_{max}} s\,(1+\tau(s)_m)^{\frac{\gamma}{1-\gamma}}\, g_c(s)$$

From (24) and (25), it is straightforward to derive an expression for the aggregate industry output in the form of Cobb-Douglas production technology as,

$$Y = (TFP)^{1-\gamma} \left(K^{\alpha} L^{1-\alpha}\right)^{\gamma} \tag{26}$$

where the aggregate TFP is defined as,

$$TFP = \left(\frac{W_n + W_m}{(V_n + V_m)^{\gamma}}\right)^{\frac{1}{1-\gamma}}$$

substituting for W_i and V_i, gives the aggregate industry TFP in terms of subsidy rates and the conditional distribution of the plant level productivity indexes.

$$TFP = \left(\frac{\kappa_n \sum_{s_n}^{s_m} s(1+\tau(s)_n)^{\frac{\gamma}{1-\gamma}} g_c(s) + \kappa_m \sum_{s_m}^{s_{max}} s(1+\tau(s)_m)^{\frac{\gamma}{1-\gamma}} g_c(s)}{\left(\kappa_n \sum_{s_n}^{s_m} s(1+\tau(s)_n)^{\frac{1}{1-\gamma}} g_c(s) + \kappa_m \sum_{s_m}^{s_{max}} s(1+\tau(s)_m)^{\frac{1}{1-\gamma}} g_c(s)\right)^{\gamma}} \right)^{\frac{1}{1-\gamma}} \tag{27}$$

In this equation, the aggregate industry TFP is the weighted average of the plant-level productivity indexes of standard and efficient producers adjusted by the subsidy rate. Equation (22), (23), and (27) are the key equations for the quantitative experiments in the next section. An important feature of equation (27) lies on the link between subsidies and the industry TFP. Without subsidies, $TFP_i = V_i$ and the industry TFP are simply the sum of TFPs of standard and efficient plants. If subsidies are given uniformly to all plants in the industry ($\tau(s)_n = \tau(s)_m$), then the aggregate TFP becomes independent of the subsidy rates and it is simplified to (28). However, any idiosyncratic subsidy directly impacts the industry TFP and leads to a larger change in the measures of productivity.

$$TFP_{(\tau(s)_i=0)} = \kappa_n \sum_{s_n}^{s_m} s\, g_c(s) + \kappa_m \sum_{s_m}^{s_{max}} s\, g_c(s) \tag{28}$$

Equilibrium

The model exhibits an equilibrium with a wage rate w, a rental rate of capital r, subsidy rates τ_i, and distribution of productivity across plants $g(s)$, such that:

1. individuals make optimal decisions on occupation choice,
2. entrepreneurs optimally choose between standard and efficient technologies,
3. allocation of labor and capital across plants is efficient,
4. markets clear,

Calibration

I calibrated the benchmark economy to India's Iron and Steel industry with no distortion ($\tau_i(s) = 0$) prior to the National Steel Policy in 2005. The period was chosen to be one year and the population was normalized to one. I followed the standard procedure to choose parameters of the production technology. The span-of-control parameter γ is set to 0.7 and α is set to 0.3. I split plants into standard and efficient producers as follows: I calculated the share of each primary input in total fuel expenditure. If a plant used coal as their primary input and if the coal expenditure accounted for at least 90% of the total fuel expenditure in that plant, I classified it as a standard plant. In contrast, If the plant used one of the other primary fuel inputs (gas, electricity, hydrocarbon), I classified it as an efficient producer. The productivity parameter of the standard and efficient technologies (κ_n and κ_m) are chosen to match the relative labor productivity of standard and efficient producers over 1999-04. Normalizing κ_n to one, the productivity parameter of the efficient technology is calculated as 1.40. This indicates that on average, the labor productivity of the efficient technology is 40% higher than the standard technology.

In an economy with no distortions, there is a simple mapping between establishment-level productivity and the size of employment (Bello et al., 2011). I estimated the distribution of plant-level productivity to match the size distribution of employment in India's Iron and Steel sector over 1999-04. The distribution is approximated by a log-normal distribution function. Since the demands for labor are linear in s, the relative productivity parameter of every two plants remains proportional to their employment sizes. I approximated the vector of plant-level productivity with a linearly spaced grid of 10000 points. Given that the average minimum and maximum number of employees in the industry are 10 and 4,000 workers, I set the minimum productivity level at s_{min}=0.01 and pinned down the maximum level of productivity at $s_{max} = 4$. Then, I approximated the mean and variance of the log-normal distribution function that corresponds to the plant-level productivity distribution. Figure 7 shows the plant-size distribution in data and its approximation by model.

$$\frac{l_{max}}{l_{min}} = \frac{s_{max}}{s_{min}}$$

To pin down the fixed technology-specific costs c_n and c_m, I set two targets: (1) the average share of managers and supervisory staff in total employees is 80%, and (2) the share of efficient producers in total employment of the industry is 33%. These targets are used to locate the lower and upper productivity thresholds in the model. Now, using the mean and variance of the productivity distribution, the model can be solved in equilibrium for technology-specific fixed

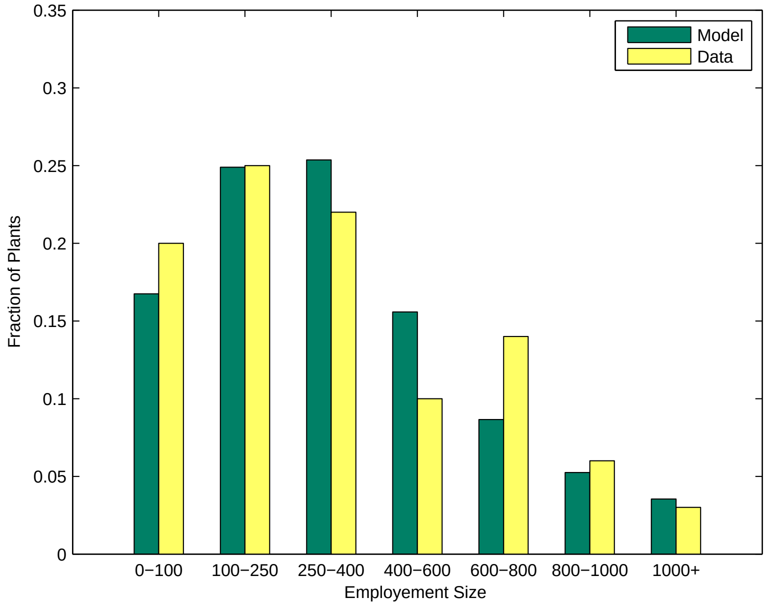

Figure 4: Distribution of Plant-level Productivity by Log-normal

costs c_n and c_m, market wage rate w, and interest rate r. Table 4 provides a summary of the parameters and targets.

Table 4: Model Calibration with Technology Choice

Parameter	Value	Targets
share of workers in total employees	0.80	from data
Employment share of efficient plants	0.33	from data
Parameter of standard technology	$\kappa_n = 1$	normalization
Parameter of efficient technology	$\kappa_m = 1.40$	relative productivity of standard and efficient plants
span-of-control	$\gamma = 0.7$	from literature
capital income share	$\alpha = 0.3$	from literature
fixed cost of standard technology	c_n=-0.0282	share of workers in total employees=80%
fixed cost of efficient technology	c_m= 0.1888	employment share of efficient producers=33%
mean of distribution function	μ= -1.62	to mach size distribution of employment
variance distribution function	σ=1.28	to mach size distribution of employment

To perform the quantitative experiments, the technology-specific costs and the mean and variance of the productivity distribution remain constant. To calibrate the subsidy policy, I constructed a subsidy vector. I computed the minimum employment size of plants with multiple production units over 1999-04. This gives the cut-off employment size of the subsidized producers at roughly $\bar{l}$=250. Any plant with minimum 250 employees receives subsidies to production. To construct the vector of plant-level subsidy, I calculated the plant-level productivity index that corresponds to 250 employees at 0.626 and define the subsidy vector as follows:

$$\tau_i(s) = \tau \text{ if } s \geq 0.626$$
$$\tau_i(s) = 0 \text{ otherwise}$$

I choose the size of subsidies as follows: The minimum and maximum disbursement of the government funds as a percentage of annual sales in Indian Iron and Steel sector between 2005 and 2008 were 0.12% and 0.16%. [9] Given that the subsidized plants produce around 70% of the aggregate output in the industry, the rates of subsidies are calculated between 0.17% (0.12/0.7) and 0.22% (0.16/0.7). [10]

Impact of Size-dependent Subsidies

The calibrated model performs well in reproducing changes in TFP growth rates and the productivity gap between producers with different technologies. Table 5 reports the outcomes of subsidies to producers with a minimum 250 employees. The policy increases the aggregate industry TFP and the the gap in TFP growth rates between plants with different technologies. The predicted changes in TFP growth rates and gap are consistent with the those directly observed from data. A subsidy of 0.17% - 0.22% to output increases the aggregate industry TFP growth by 0.57-%-0.75% which contributes to 16% to 21% of the industry TFP growth reported by the data (around 1/5 of the observed aggregate TFP growth). The model also predicts that the policy would lead to a 1.50%-1.91% gap in TFP growth between standard and efficient producers which account to 44% to 56% of the actual productivity gap in the industry calculated from data.

Table 5: Average Annual TFP Growth Rates and Gap; (%)

	Industry	TFP growth gap between standard and efficient plants
$\tau_{min} = 0.17\%$	0.57	1.50
$\tau_{max} = 0.22\%$	0.75	1.91

[9] Indian Ministry of Steel, Annual Report 2011-12.

[10] In India's Iron and Steel industry, subsidies are reported as a share in R&D investment and R&D investment is reported as a percentage of annual sales turnover. Annual turnover is the gross amount of sales received by plants. In contrast, the value of output represents the total value of turnover in an accounting period plus the value of other incomes including income from industrial, non-industrial services, variation in the stock of semi-finished goods, value of electricity generated and sold, value of own construction, net balance of goods sold in the same condition as purchased, and sale value of goods sold in the same condition as purchased. In my sample, the value of turnover and the value of output are roughly the same, so, to conduct the experiments, I consider subsidies as percentage of output.

Output Change

Table 6 reports the impact of the size-dependent subsidies on aggregate industry output and output of plants with standard and efficient technologies. The idiosyncratic policy leads to 0.23%-0.29% increase in the aggregate industry output per year. The policy also increase output of efficient producers by 1.72%-2.20% and reduce output of standard producers by 2.037%-3.05% (average per year).

Table 6: Average Annual Output Growth Rates; (%)

Industry	Standard Producers	Efficient Producers
$\tau_m = 0.17\%$ 0.23	-2.37	1.72
$\tau_m = 0.22\%$ 0.29	-3.05	2.20

I identify three direct effects through which the size-dependent subsidies impact the aggregate TFP growth and the gap in growth rate of plants with standard and efficient technologies. (1) misallocation effect: the subsidy introduces idiosyncracy in the prices faced by individual producers, causing a reallocation of resources from non-subsidized to subsidized plants, (2) technology upgrade effect: the plants that receive the subsidies switch from the standard to the efficient technology, (3) selection effect: through general equilibrium effects, who becomes worker and entrepreneur and what technology each entrepreneur decides to use also impacts the aggregate industry TFP.

Misallocation Effect

In the standard literature, the misallocation effect is expected to reduce aggregate TFP. To measure the quantitative significance of misallocation in my framework, I shutdown the endogenous technology choice. I re-calibrate the model to a new environment in which only one technology was available for production. The only decision for individuals is to choose between being a hired worker or an entrepreneur. For simplicity, the technology specific parameter κ is normalized to one. In the above environment, there is only one threshold of skills that determines allocation of individuals between workers and entrepreneurs. The rest of the calibrated parameters and the approximation of the productivity distribution remain unchanged. Table 7 shows parameter of the model in the environment with one production technology.

The policy is still to subsidize plants with a minimum of 250 employees. Therefore, the subsidy vector remains the same too. Since, the subsidies are given to the large plants, the profit

Table 7: Model Calibration Without Technology Choice

Parameter	Value	Targets
share of workers in total employees	0.80	from data
technology-specific parameter	κ= 1	normalization
span-of-control	γ= 0.7	from literature
capital income share	α= 0.3	from literature
fixed cost of standard technology	c= 0.0243	share of workers in total employees=80%
mean of distribution function	μ= -1.62	to mach size distribution of employment
variance distribution function	σ=1.28	to mach size distribution of employment

of plants with a productivity index closed to the threshold of skills remains unchanged. The following equation is used to calculate the aggregate TFP. To control for the general equilibrium effect, I hold the total number of entrepreneurs fixed. The policy leads to a reallocation of resources from non-subsidized plants to subsidized plants (larger units) causing misallocation. The impact of 0.17%-0.22% subsidies to output on aggregate TFP is reported in Table 8. The misallocation effect should cause a 2% decline in the observed aggregate TFP growth in the industry.

$$TFP = \left(\frac{\sum_{s_{min}}^{s_{max}} s(1+\tau(s)_n)^{\frac{\gamma}{1-\gamma}} g_c(s)}{\left(\sum_{s_{min}}^{s_{max}} s(1+\tau(s)_n)^{\frac{1}{1-\gamma}} g_c(s)\right)^{\gamma}} \right)^{\frac{1}{1-\gamma}}$$

The proportional increase in the output of subsidized plants is less than the proportion increased in the inputs employed by those plants. The policy leads to a small decrease in the aggregate TFP as the subsidies are given to more productive producers in the industry (there is a negative correlation between the misallocation effect and productivity levels of plants that are hit by distortions).

Table 8: Misallocation Effect; (%)

	Industry TFP
$\tau_m = 0.17\%$	-0.01
$\tau_m = 0.22\%$	-0.04

Technology Upgrade Effect

A part of the productivity growth is attributed to the technology upgrading at plant level. The technology selection is determined by the level of plant productivity as well as the technology-specific costs. The subsidies incentivize plants to adopt the efficient technology that is more productive. To measure the technology upgrade effect, I held the total number of plants unchanged and calculated the productivity gain generated from the technology switch only. The model predicts that the technology upgrading effect contributes to 49% of the aggregate TFP growth calculated from data.

There is strong supporting evidence of technological change in India's Iron and Steel industry over the last decade. Iron and steel making processes are extremely intensive in the use of material and energy. The Iron and Steel producers were faced with a wide range of technologies that were fundamentally characterized by energy usage. For example, an Open Hearth Furnace (OHF) is an inefficient technology introduced in 1850's in India. Most OHFs have been closed due to their fuel inefficiency and are being replaced by other technologies such as the Basic Oxygen Furnace (BOF). According to India's Iron and Steel industry Annual Report, technology replacement reduced the average share of the OHF in the total steel production in India from 16.6% over 1999-2004 to less than 2% in 2005-08 (Table 9). In addition, in recent years, a number of smaller units equipped with the Electric Arc Furnace (ERF) have invested in capacity expansion projects and increased their level of production.[11]

Table 9: Share of Technologies in Crude Steel Production, %

	1999-2004	2005-2008
Efficient technology (BOF)	50.8	41.4
Efficient technology (EAF)	32.6	56.6
Standard technology (OHF)	16.6	2.0

The evidence of technological change can also be observed from fuel expenditures in the industry. The technological change would be expected to reduce consumption of coal as an inefficient input in the industry. Table 10 reports the share of coal, electricity, and other fuels as the main primary inputs in total fuel expenditures from 1999-04 to 2005-08 using the ASI data. The share of coal in total fuels expenditures decreased from 24.3% to 21% while share of other fuels increased from 14% to 17% during the same period.

Table 10: Share of Primary Fuel Inputs in Total Fuel Expenditures, %

	1999-2004	2005-2008
Efficient Fuels (gas, electricity, hydrocarbon)	75.7	79.0
Inefficient Fuel (coal)	24.3	21.0

[11]Source: Statistics Archive, World Steel Association.

Selection Effect

The choice of occupation for individuals and choice of technology for entrepreneurs were directly influenced by the industry wage rate and the expected profit of entrepreneurship with a given technology. A higher wage rate makes the labor market more attractive than entrepreneurship. On the other hand, the expected profits in the industry depend directly on establishment-level productivity and the size of subsidies. Since the subsidies were given only to large producers, the expected profit earned by small plants remained unchanged while the wage rate went up. The entrepreneurs with the lowest managerial ability changed their occupation and become hired workers. This increased the average plant size and market share of the surviving plants. In addition, the subsidies changed the upper threshold level of skills and increased the size of efficient plants throughout the industry. The overall general equilibrium effect is such that the aggregate industry TFP increased. The model predicts that the selection effect would contribute to 53% of the aggregate TFP growth in the industry.

Table 11 reports changes to the average plant size in India's Iron and Steel industry as observed from the ASI data and predicted by the model before and after the policy change in 2005. The subsidy policy explains about 15% of the increase in the average number of workers per plant in the whole industry, and 40% and 27% of the decrease/increase in the average number of workers in standard and efficient plants respectively.

Table 11: Change in Average Number of Workers in Each Plant; Model vs. Data

	Data	Model
Total Industry	11%	1.7%
Standard Producers	-8%	-3.4%
Efficient Producers	17%	4.6%

Overall, the share of each channel in the aggregate TFP growth is summarized in Table 12.

Table 12: Sources of TFP Growth (%)

	Model
Misallocation Effect	-2.0
Technology Upgrade Effect	49.0
Selection Effect	53.0

7 Conclusion

This study examined the impact of distortions generated by size-dependent subsidies that lead to misallocation but encouraged technology adoption at establishment level. The focus of my study was on a particular industry policy in which the link between the observed policy and productivity outcomes was tight. My study found that an endogenous improvement in the establishment-level productivity induced by size-dependent subsidies can dominate the misallocation effect and lead to an increase in aggregate TFP.

I focused on subsidies that were given under the National Steel Policy initiated in 2005 in India's Iron and Steel sector. The policy was size-dependent in practice and only large Iron and Steel plants received the subsidies. My growth accounting using the ASI plant-level data shows that India's Iron and Steel industry experienced a high TFP growth during 1999-08 and especially after the policy change in 2005. The average growth rate of TFP increased from 1.72% over 1999-04 to 3.61% over 2005-08. The main source of the TFP growth was within-plant efficiency rather than reallocation. I identified technology change as a good candidate to explain the within-plant efficiency growth. Through a technology split exercise, I classified plants into standard and efficient versions that differed in their level of fuel efficiency (technology productivity) and technology-specific costs. Through a technology-wise growth accounting, I showed that only plants with efficient technology grew faster after the policy change and that the TFP of standard producers actually declined over 2005-08. Furthermore, productivity decomposition showed that the TFP growth rates of both standard and efficient producers were attributed to within-plant efficiency, however, there was a speedup in reallocation across plants with standard technology especially in 2005-08: the share of reallocation in aggregate TFP growth of the standard producers has increased from 8.9% in 1999-04 to 33.9% in 2005-2008.

I extended the Lucas (1978) span-of-control model to include a technology choice at the establishment-level along the lines of Adamopoulos and Restuccia (2012) and calibrated it to the plant-level data prior to the policy change in 2005. Without the technology change, the model might produce the misallocation effect through a small TFP loss. However, when the technology upgrade was allowed, the model showed that the size-dependent subsidies to plants with minimum 250 employees rose industry TFP growth by 0.63%-0.71% which explains about 16%-21% of the observed TFP growth from data. While, the misallocation effect had a negative impact on the aggregate TFP growth, the technological upgrade and selection effects were the source of TFP growth in the industry.

Overall, the findings of this study contribute to a deeper understanding of the distortions that generate the misallocation effect but impact establishment-level productivity at the same time. My findings are consistent with previous empirical works on misallocation if the technology upgrade channel is shutdown. However, if distortions induce a technology upgrade at establishment-level, then an increased establishment-level productivity can enhance the TFP at the aggregate level.

My study cannot ignore the inefficiency associated with the idiosyncratic policy. Distortions generated from size-dependent subsidies affect the optimal distribution of resources across plants. Less productive producers may become inefficiently large and adopt technologies that are more skill intensive. The lack of technical skills among entrepreneurs with lower level of abilities may create a serious impediment to a successful implementation of the new technologies. This study did not take into account the other source of TFP growth in the industry. The Indian manufacturing sector has experienced major liberalization policies in the last two decades that could potentially have impacted measures of productivity too.

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Appendix A: Iron and Steel Making Technologies

The Indian Iron and Steel industry has experiences a remarkable growth since 1990s. India was the fifteenth largest steel producer in the world in 1998. In 2013, India has become the 4th largest crude steel producer and the world's largest producer of direct reduced iron. The following graph shows share of India in the world production of crude steel.

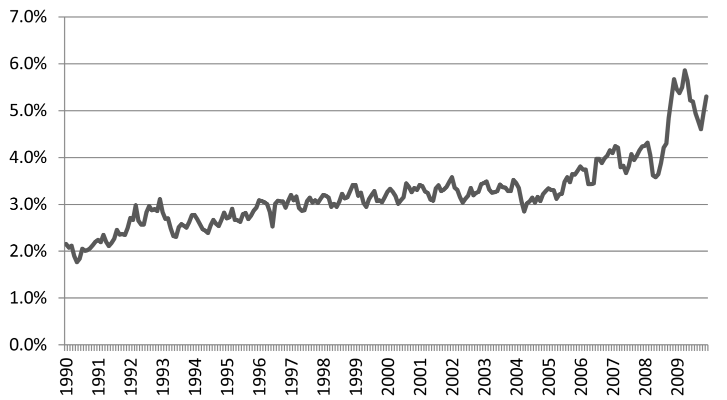

Figure 5: Share of India in the World Production of Crude Steel (%)

The Iron and Steel industry heavily depends on the production technology and process. Around 70% of total steel production in the world is through Basic Oxygen Furnace (BOF), 28.8% by Electric Steel Making (EAF&EIF) and the balance 1.2% through the Open Hearth Furnace (OHF). The open hearth route is an inefficient technology and almost extincts in most of steel producing countries. In terms of production units, there are two types of steel producers: (1) primary or integrated producers and (2) secondary producers. In the integrated units, Pig Iron and Sponge Iron are produced from iron ore first and then they are converted to crude steel. Crude steel is used further for rolling, casting, blooming, slabbing, or coating products. Integrated producers in India use Blast Furnace (BF) and Direct Reduced (DR) technologies to produce iron and Open Hearth Furnace (OHF) and Basic Oxygen Furnace (BOF) to produce steel.

In the terms of energy inputs, coal and gas are the main inputs in the primary Iron and Steel making process. In particular, coal is the main energy for blast furnace and open hearth furnace while liquid hydrocarbons are used in direct reduced and Basic Oxygen Furnaces. Secondary units produce steel from sponge iron or steel scrape using electric arc furnace (EAF) or electric induction furnace (EIF). Electricity is the main energy in these production root.

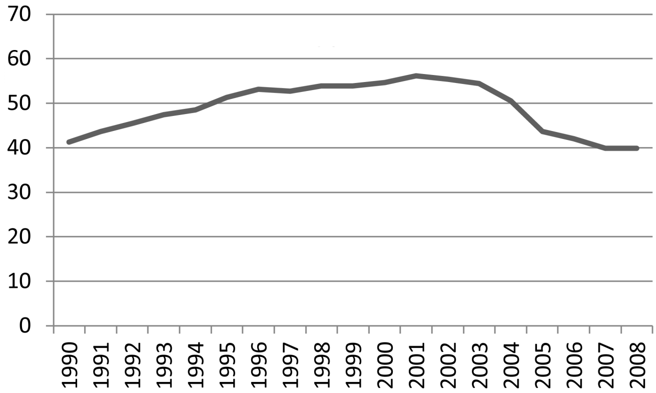

Figure 6: Share of Basic Oxygen Furnace in Steel Production in India (%)

Basic Oxygen Furnace is the main large scale technology to produce steel. The average share of Basic Oxygen Furnace in production of crude steel in India has decreased from 50.8% in 1990-04 to 41.4% in 2005-08.

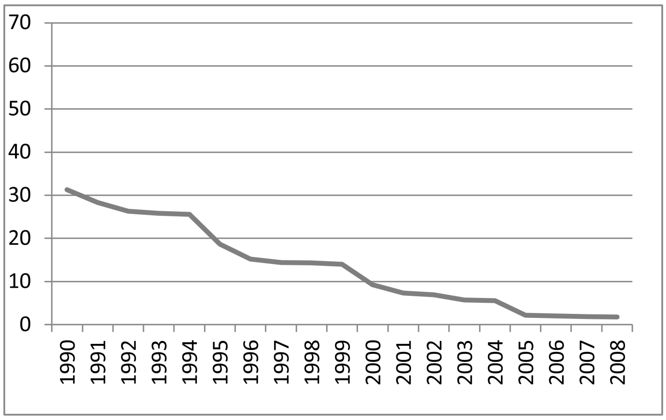

Figure 7: Share of Open-Hearth Furnace in Steel Production in India (%)

Open-Hearth Furnace is characterized by low efficiency and quality of output. In many steel producing units in India, Open-Hearth Furnaces are shutdown or replaced by newer technologies. The average share of crude steel production by OHF in India has decreased from 16.6% in 1990-04 to 2% in 2005-08.

Electric Arc Furnaces range in size from small to large units and are used for secondary steelmaking. The average share of this technology has increased from 32.6% in 1990-04 to 56.6% in 2005-08.

Steel is produced through a complicated processes involving many stages and yielding thou-

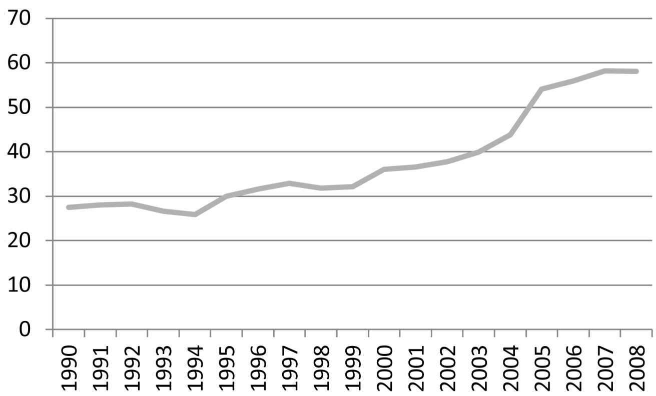

Figure 8: Share of Electric Furnace in Steel Production in India (%)

sands of by-products. Steel is produced from either steel scrap or iron ore. On the basis of production technology, Iron and steel producers are classified to two types of producers: integrated producers and secondary producers. Integrated producers are large units with advanced technologies that operate ore and coke mines. They produces iron ore in the iron-making process and then use iron ore to produce steel. Integrated steel units traditionally have captive plants for iron ore and coke, which are the main inputs to these units.[12] In contrast, the secondary producers are mini-steel plants. They make steel by melting scrap or sponge iron or a mixture of the two. The secondary steel producers use less complicated technologies and electricity is the main input. For the both producers, material and the process substantially affect quality of steel and the total energy consumed during production.

In the iron-making step, ore is reduced to either pig iron or sponge iron. Pig iron production occurs in blast furnaces where coke is the primary fuel. Sponge iron is produced by direct reduction (DR) processes using fossil fuels and coal. The conversion of ore into pig iron is the most energy-intensive stage of steel making. In a conventional integrated steel plant, pig iron is produced in a blast furnace, using coke in combination with injected coal, oil, or gas. Blast furnaces are operated at various scales, ranging from mini-blast furnaces to large furnaces. Sponge iron, produced by direct reduction (DR) processes, has different properties from pig iron. In the DR process, iron is produced by reducing the ores using syngas from different fossil fuels (mainly oil or natural gas; in India coal or gas based) in small-scale plants. DR iron (or sponge

[12]Currently there are three main integrated producers in India namely Steel Authority of India Limited (SAIL), Tata Iron and Steel Co Ltd (TISCO)and Rashtriya Ispat Nigam Ltd (RINL)

iron) serves as high quality alternative for scrap in secondary steel-making. Steel-making is the reduction of the amount of carbon in the hot iron metal to a level below 1.9 percent through the oxidation of carbon and silicon.

Primary Steel Producers

Most primary steel is produced by two processes: open hearth furnace (OHF) and basic oxygen furnace (BOF). While OHF is an older technology and uses more energy, this process can also use more scrap than the BOF process. However, BOF process is rapidly replacing OHF worldwide because of its greater productivity and lower capital costs. In addition, this process needs no net input of energy and can even be a net energy exporter in the form of BOF-gas and steam. The process operates through the injection of oxygen, oxidizing the carbon in the hot metal. Several configurations exist depending on the way the oxygen is injected. The steel quality can be improved further by ladle refining processes used in the steel mill.

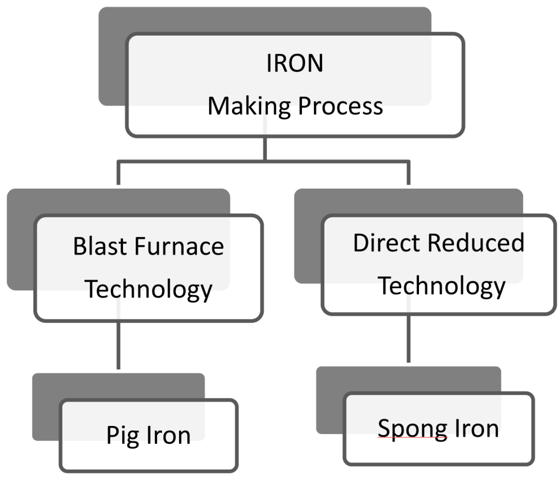

Figure 9: Iron Making Technologies

Secondary Steel Producers

Secondary steel is produced in an electric arc furnace (EAF) using scrap. In secondary steel production, the scrap is melted and refined, using a strong electric current. Steel making based on external scrap (scrap from outside the steel sector) requires less than half as much primary energy as steel made from ore.

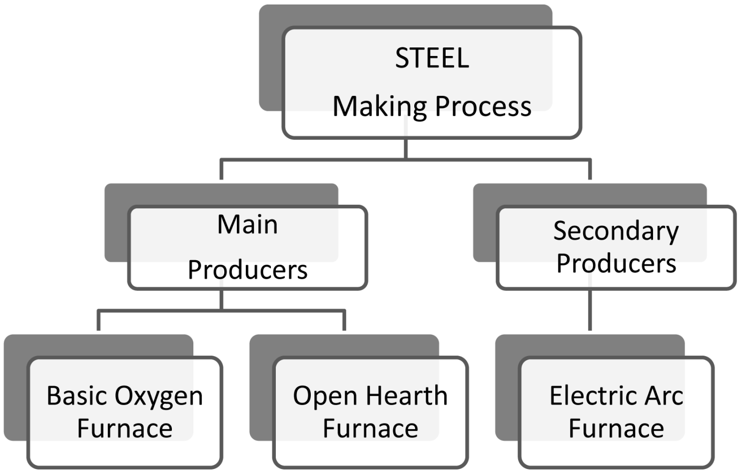

Figure 10: Steel Making Technologies

In a continuous steel casting process, liquid steel is directly cast into semi-finished products. The semi-finished steel is fed in to re-rolling mills to get finished steel products. Finished steel products are classified in to two types of finished carbon steel or finished alloy steel. Long products are bars, rods, channels, angles and other structural materials are finished carbon steel. Finished steel products are used in the construction and engineering industry and, to some extent, in the manufacturing sector. Flat products also another type of carbon steel consist of sheets, coils and plates. Alloy steels can be further classified into two categories of stainless steel and alloy steels.

Appendix B: Annual Survey of Industries (ASI)

The Annual Survey of Industries (ASI) is the principal source of industrial statistics in India. It provides statistical information to assess and evaluate, objectively and realistically, the changes in the growth, composition and structure of organized manufacturing sector comprising activities related to manufacturing processes, repair services, gas and water supply and cold storage. The Survey is conducted annually under the statutory provisions of the Collection of Statistics Act 1953.

The definition of census and sample have been changed several times after the first ASI in 1986. The first coverage of the survey under census sector was all units with 50 or more workers operating with power, and units having 100 or more workers operating without power. The procedure continued until ASI 1986-87 by which time the total number of factories in India grew enormously. Accordingly, the definition of the census sector was changed from ASI 1987-88 to the units having 100 or more workers irrespective of their operation with or without power. This design continued until ASI 1996-97. In 1998, to maintain the budget limit a new sampling design was adopted in ASI 1997-98. The census sector was redefined to include units having 200 or more workers and significant industrial units having less than 200 workers. This approach significantly reduced the sample size in ASI 1997-98 compared to that of ASI 1996-97 while maintaining a fair level of degree of precision for the estimates up to the state level. In 2005, following the decision taken in the Standing Committee on Industrial Statistics (SCIS), the sampling design for ASI 2004-05 to ASI 2008-09 changed again and covered units with 100 or more workers as census sector and the rest of the units as sample sector, without any change in the existing criteria.

Table 13: Sampling Design of Census Sample Criteria

Coverage	Criteria
ASI 1980-81 to ASI 1986-87	100 or more workers 50 or more workers with power All plants in 12 industrially backward states
ASI 1987-88 to ASI 1996-97	100 or more workers (with or without power) All plants in (same) 12 industrially backward states
ASI 1997-98 to ASI 2003-04	200 or more workers Selected "Significant Units" with fewer than 200 workers which "contributed significantly to the Value of Output" in ASI data between 1993-94 and 1995-96 All plants in (same) 12 industrially backward states All public sector undertakings
ASI 2004-05 to ASI 2008-09	100 or more workers All plants in 5 industrially backward states

Appendix C: National Industrial Classification(NIC)

The first National Industrial Classification in India adopted in 1959. With effect from ASI 1973-74, the National Industrial Classification (NIC) 1970 developed based on UNISIC 1968. NIC has been revised several times due to the industrial development in India and other administration issues. The following table outlines National Industrial Classification (NIC) and its coverage since ASI 1973.

Table 14: India National Industrial Classification (NIC)

National Industrial Classification	Coverage
NIC 1970	ASI 1973-1974 to ASI 1988-1989
NIC 1987	ASI 1989-1990 to ASI 1997-1998
NIC 1998	ASI 1998-1999 to ASI 2003-2004
NIC 2004	ASI 2004-2005 to ASI 2009-2010

The 5-digit National Industry Classification (NIC) codes of Iron and Steel Industry is outlined in the following table.

Table 15: Basic Metals, National Industry Classification (NIC), 5-Digit Codes

Description
27110 ferro alloys.
27120 Direct Reduced Iron (DRI)/ Sponge Iron
27130 Pig Iron
27141 semi -finished non ally steel of these shapes
27142 semi -finished alloy steel of these shapes
27143 semi -finished stainless steel of these shapes
27151 alloy-steel of these shapes
27152 non-alloy steel of these shapes
27153 stainless steel of these shapes
27161 non-alloy steel hot rolled flat products
27162 alloy steel hot rolled flat products
27163 stainless steel hot rolled flat products
27164 non-alloy steel cold rolled flat products
27165 alloy steel cold rolled flat products
27171 GP/GC/Zn-Al. coated sheets/ Color coated
27172 Tinplate
27173 Tin Free Steel
27181 non-alloy steel wires
27182 alloy steel wires
27183 stainless steel wires
27184 wires coated with zinc or other materials
27190 other basic iron and steel n.e.c.