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PRODUCTION FLEXIBILITY, MISALLOCATION AND TOTAL FACTOR PRODUCTIVITY

Burak R. Uras
Ping Wang

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ABSTRACT

Economy-wide institutional deficiencies causing factor misallocation have been emphasized as essential determinants of aggregate TFP differences. This paper argues that production flexibility at the micro-level is an economic characteristic that should be given priority in TFP aggregation exercises. We investigate a heterogeneous firms model with two distinct notions of flexibility: (i) the firm-specific capacity to optimize over a set of production techniques that serve to organize capital and labor; and, (ii) the industry-specific substitutability between efficient units of capital and labor. We show the presence of a strong interaction between "ability to choose techniques" and "input substitutability": high complementarity at the industry-level amplifies imperfections associated with techniques choice at the firm-level. Using the micro-founded structure, we develop measures for factor, output and technique distortions across a distribution of firms and quantify their TFP effects. For a broad range of U.S. manufacturing industry clusters, technique distortions generate more TFP losses than misallocation resulting from capital and output distortions, with larger TFP gains from removing technique distortions in industries that exhibit high degrees of factor complementarity. Our key quantitative results are robust to outliers, production function specification, mismeasurement and parameterization of the model and are strongly present in developing country datasets.

Burak R. Uras
Department of Economics
Tilburg University
Tilburg, The Netherlands
r.b.uras@uvt.nl

Ping Wang
Department of Economics
Washington University in St. Louis
Campus Box 1208
One Brookings Drive
St. Louis, MO 63130-4899
and NBER
pingwang@wustl.edu

"Why Are Total Factor Productivities Different? My candidate for the factor is the strength of the resistance to the adoption of new technologies and to the efficient use of currently operating technologies, and this resistance depends upon the policy arrangement a society employs. What is needed is a theory of how arrangement affects total factor productivity." [Prescott (1998, p. 549)]

1 Introduction

Thanking to the increased availability of reliable micro datasets, there is a growing literature over the past decade uncovering the sources and the aggregate consequences of factor and output-misallocation across firms.[1] This literature not only helps explaining productivity gaps across countries, regions as well as sectors, but also provides valuable policy prescriptions for means to advance a macroeconomy. While many studies have concluded with sizeable aggregate gains to be obtained from improving allocative efficiency, the findings have recently been challenged in the aspects of adjustment costs, overhead costs, heterogeneous demand elasticicities, and measurement errors.[2] In this paper, we focus on a dimension which has remained largely unexplored in the literature to address the following question: what is the role of the degree of micro-level interactions between production factors, which is broadly defined as *production flexibility* by economists and as *flexible manufacturing systems* (FMS) by management scientists, in explaining the macroeconomic consequences of allocative efficiency?

The study of production flexibility in economics can be traced back to Stigler (1939) who advocates flexibility as a competitive advantage especially for smaller firms unable to reach the necessary scale for cost minimization. The concept of production flexibility has not gained much attention in academics until the revolutionary production process developed by Toyota in late 1970s and early 1980s for combating rising costs as a result of oil crises – a process broadly referred to as flexible manufacturing system.[3] In their now-classic work, Milgrom and Roberts (1990 and 1995) stress that, due to the advantages brought by integrated production technologies, for many firms flexibility has become an integral part of the fundamental logic in modern manufacturing.[4] Building upon this literature, Bresnahan, Brynjolfsson and Hitt (2002) further observe that "firms do not

[1]See Restuccia and Rogerson (2013) and Hopenhayn (2014) for comprehensive survey of the literature.

[2]See Asker, Collard-Wexler and de Loecker (2014), Bartelsman, Haltiwanger and Scarpetta (2013), Song and Wu (2015), and Bils, Klenow and Ruane (2017), for each of the four aspects, respectively.

[3]This concept is sometimes referred to as "lean" or "just-in-time" production (see Womack, Jones and Roos (1990) and Shah and Ward (2007), respectively).

[4]Milgrom and Roberts (1990) provide, among others, two leading examples: (i) "Ford's factories is being replaced by flexible machine tools and programmable, multi-task production equipment" (p. 511); and, (ii) "General Electric has reduced the design and production time it takes to fill an order for a circuit-breaker box from three weeks to three days" (p. 512).

simply plug in computers or telecommunications equipment and achieve service quality or efficiency gains. Instead they go through a process of organizational redesign" (pp. 340-341). This strand of research therefore elaborates that high manufacturing flexibility implies ability to design (and re-design) firm-specific blue-prints before initiating production processes which can improve upon the competitiveness of a firm by exploiting the interactions between factors of production. In this paper, we are after to formally embed such micro-level interactions borne by manufacturing flexibility - and especially its implications for firm-specific choice of blue-prints - into a quantitative macro-framework.

To address the important set of questions raised above, we develop a generalized production framework in which we allow for firm-and-industry level components of production flexibility that *serve to organize raw measures of factors efficiently.* While developing this model-framework we adopt the terminologies in the literature on the microfoundation of the aggregate production function pioneered by Houthakker (1955-1956) and revived by Kortum (1997) and Jones (2005), namely firm-specific blue-prints or *production techniques.*[5] We allow production techniques to be endogenously determined by firms' decision makers, which we define as firm-level flexibility in customizing a production-line. We also utilize the concept *industry-specific elasticity of technique-augmented factor substitution* to govern the process of flexibility at the aggregate level, which we will refer as (aggregate or industry-wide) production flexibility for the rest of the paper.

In order to capture firm-specific limitations to flexibly choose the most appropriate blue-prints, we also incorporate the element of technique distortions into the framework. What we have in mind is that before hiring factors of production a firm needs to establish a "unique business plan". The implementability of such idiosyncratic processes at early stages of the production-line are in general subject to uncertainty, limited information and resistance – as motivated in the management science literature. For instance, as pointed out by Fine and Freund (1990), "available tools for considering cost/benefit tradeoffs for investments in flexible automation often contradict the intuition of their managers" (p. 449). Pailles, Yannou and Bocquet (1996) stress that "despite the popularity of Flexible Manufacturing, managers still use inadequate recipes to efficiently incorporate flexibility into their strategic decisions" (p. 79). Most importantly, Siggelkow (2002) echoes "in complex systems, firms' decision makers may *not* always have a precise understanding of the *exact strength of the interaction between activities* ... incentive and accounting systems may lead decision makers to ignore or misperceive interactions" (p. 900, emphasis added).

To account for inflexible techniques choice at the firm-level – that could be borne due to limited understanding of the interactions between factors of production or resistance to adopt certain tech-

[5]A primary focus of this line of research has been on qualifying the shape of the aggregate production function based on the distribution of production techniques or on the adoption or assimilation of a global frontier technology by local firms.

niques – we allow for structural *mistakes* (distortions) in operational production techniques. These distortions force firms to deviate from operating at the most-efficient combination of techniques that could be chosen from the menu of blue-prints. Formally, in our model techniques choice will be subject to mistakes which are *ex ante* not *perceivable* or *foreseeable*. This means after a technique combination is chosen and before hiring factors, the owner of the firm realizes that its operational capital-technique may turn out to deviate from an optimal benchmark.

In our framework while we allow firms to differ in technology frontiers, factor and output distortions, as well as techniques-choice distortions, we allow industries to differ in substitutability between technique augmented production factors. By developing a structure to aggregate these heterogeneous firms to produce an industry-level total factor productivity measure, we are able to isolate, both theoretically and quantitatively, the TFP effects of factor and output misallocation from that of technique distortions. To be more specific, we study a manufacturing firm producing with the use of two factor inputs, capital and labor. Each input is augmented by a factor-specific production technique. The two production techniques are chosen from a technology menu, depending on the technology scale measuring the information capacity and capability of the firm's decision makers. The two technique-augmented factor inputs are then combined in a constant elasticity of substitution (CES) form to produce the output. As a key property of this benchmark framework, we derive a positive association between industry-level factor substitutability and the cost efficiency of the firm: Flexible substitutability between technique-augmented factor inputs reduces the unit cost of production. This result echoes the industry-level evidence documented in the management science literature that we will summarize in Section 2.

Building upon this generalized production framework, we then incorporate distortionary frictions into the firm's factor, output and techniques decisions. For better comparison with previous studies, the factor and output frictions are modelled as distortionary "taxes". The *technique choice friction* – new to the literature – is a distortion resulting from firm-specific technique inflexibilities, as delineated above. The key theoretical result shows that while all three distortions, as expected, reduce the efficiency of the firm as well as the aggregate TFP, we establish another key property. *Low flexibility of production, or a high degree of complementarity between factors, amplifies the cost distortions arising from technique mistakes.* This finding also confirms a key conclusion from the management science literature: Siggelkow (2002) argues that misperceiving interactions should be regarded of particular importance especially for complementary activities in a firm.

Furthermore, our model also predicts a particular correlation between two structural (endogenous) wedges that technique distortions influence: specifically, capital and output wedges that are augmented by technique distortions would be negatively correlated with each other if firms face distortions to their technique decisions. We refer to Compustat North America database and show that such a negative correlation is significantly visible in firm-level data.

Upon establishing the theoretical implications of techniques choice and the potential consequences of technique mistakes for firm-level performance, an immediate question arises: Is this new mechanism quantitatively important for explaining TFPs across a distribution of manufacturing industries? To address this question, we utilize firm-level balance sheet data for publicly traded firms from Compustat North America, in conjunction with industry-level production parameters, to separately back out manufacturing firms' capital, output and technique distortions. We then measure firms' physical and revenue productivities (TFPQ and TFPR, respectively). By aggregating over a heterogeneous firms distribution, we construct a deep-structural measure of industry-level TFP to examine the consequences of capital, output and technique distortions. And to this end, because we measure TFP directly without relying on a particular assumption on the joint distribution of TFPQ and TFPR, we also eliminate the associated measurement issues pointed out by Bils, Klenow and Ruane (2017).

Using the quantitative framework, we conduct counterfactual exercises to measure the impact of each source of distortion for industry TFPs – in particular, the role of flexibility played in explaining aggregate efficiency losses. Our quantitative experiments yield several important insights. First, for a variety of manufacturing industry-clusters technique distortions and output distortions account for much more substantial efficiency losses at the level of industry TFPs than capital distortions. Second, the impact of technique distortions in generating efficiency losses in the aggregate is in general larger than that of output distortions. Third, the inefficiency impact of technique distortions get mitigated by the industry-wide flexibility of production, i.e. TFP gains from removing technique distortions are substantially smaller in industries where factors are highly substitutable. Fourth, capital distortions are negligible for industry-level TFPs – matching the findings of past research, which utilized publicly-traded firm data. Fifth, the key quantitative findings – that technique distortions are significantly more important than capital finance distortions and at least as important as output distortions for industry TFPs – are robust to the measurement of firm-level productivity, parameter specifications, outliers and the mismeasurement of capital-stock and cost of capital variables.

We also repeat our quantitative experiments for India and China. Cross-country comparisons developed using Chinese and Indian firm-level data show that technique distortions are substantial for industry-TFPs in these two developing countries as well.

Our results echo the Lawrence Klein Lecture delivered by Prescott (1998): TFP differences depend crucially on *the strength of the resistance to the efficient use of currently operating technologies*. The underlying policy arrangement causing such resistance is captured in our framework by the technique distortions and the resulting variation in such distortions due to intra-industry technique misperception, which are shown to be essential for the aggregate industry productivity.

Related Literature The paper is related to three strands of literature. One strand is on understanding the sources of misallocation and its consequences for aggregate productivity. Another strand is on the introduction of factor-specific production techniques to qualify the shape of the aggregate production function and to investigate the adoption or assimilation of a global frontier technology by local firms. The third strand is the business and organization literature that aims to understand the role of flexibility for firm performance. We delineate our contribution to each strand as follows.

The first strand of literature goes back to Banerjee and Duflo (2005) who identify the large dispersion in the marginal product of capital among firms in India as an important source for underperformance in overall output. More closely related to our paper are Restuccia and Rogerson (2008) and Hsieh and Klenow (2009). Restuccia and Rogerson (2008) show that when factor and output distortions hit physically productive firms, this has quantitatively important consequences for the total factor productivity of the macroeconomy. Hsieh and Klenow (2009) find that when the dispersion in production distortions are alleviated in India and China to the extent of the U.S., the TFP gap between the U.S. economy and these two countries could shrink up to 40%. Jones (2013) further elaborates that misallocation at the micro level leads to lower TFP at the macro level, thereby helping explain cross-country TFP gaps. To understand the sources of misallocation, Banerjee and Moll (2010), Midrigan and Xu (2013), Buera and Shin (2013) and Moll (2014) construct dynamic general equilibrium models of misallocation with capital market imperfections, whereas Jovanovic (2014) studies misallocation using an assignment framework with heterogeneous firms and workers. Finally, using a measured TFP approach and secondary bond price data for publicly traded firms from the U.S., Gilchrist, Sim and Zakrajsek (2013) provide evidence for that removing the dispersion in borrowing costs observed in the bond-price data for U.S. manufacturing firms would improve the TFP of the manufacturing industry only by 1-2 percentage points.

We also work in an environment of factor misallocation, where firms face factor input distortions *à la* Restuccia and Rogerson (2008) and Hsieh and Klenow (2009). Yet, we go beyond by incorporating a structure to study distortions to production techniques and quantify the substantial impact of technique distortions on industrial TFPs using data from publicly traded firms. Moreover, with our emphasis on production flexibility, we generalize the Cobb-Douglas production function commonly used in the literature by allowing different non-unity elasticities of substitution for firms in different industries. Importantly, we also confirm the findings of Gilchrist, Sim and Zakrajsek (2013) by showing that for publicly traded firms removing capital distortions would have negligible effects for industry-level TFPs.

The second strand of literature owes to the seminal work by Houthakker (1955-1956), where firms produce using different Leontief technologies (local production) with production techniques following a Pareto distribution. The aggregate (global) production across production units then exhibits the Cobb-Douglas form. Kortum (1997) shows that if researchers sample production techniques from Pareto distributions, then productivity growth is proportional to the growth of the research stock and accounts for the empirical regularities concerning productivity growth and researcher employment observed over the past 50 years. Jones (2005) generalizes Houthakker's result and shows that as long as the techniques arrive to firms following a Pareto distribution, firms' global production would be Cobb-Douglas. Wang, Wong and Yip (2014) develop a technology assimilation framework using the global technology approach and show that the lack of assimilation of the frontier technology can be instrumental for differentiating between trapped and growth miracle economies. Also related to our paper is the framework of Caselli (1999), Acemoglu (2003), and Caselli and Coleman (2006). In Caselli (1999), firms decide both on production factors and techniques, whereas in Acemoglu (2003) firms undertake both labor- and capital-augmenting technological improvements. Caselli and Coleman (2006) investigate the implications of endogenous techniques choice for the cross-country technology frontier.

As in this second strand of literature, we also explore an alternative production framework incorporating the concept of production techniques at the firm level. However, we differ by modeling techniques choice under a generalized CES framework with a distribution of firms heterogeneous in their technology frontiers as well as in capital, output and technique distortions. Thus, we are able to highlight the role of production flexibility for TFP aggregation exercises as well as to differentiate the implications of technique distortions from those of conventional sources of factor and output distortions.

Third, there is a also vast literature on production flexibility in addition to those cited in the Introduction. The literature highlights "insurance" and "strategic competitiveness" roles of FMS. To the end of insurance role, including Fine and Freund (1990), Fine (1993) and Netessine, Dobson and Shumsky (2002), many have argued that managers see flexibility as an adaptive response when hedging against uncertain environments (factor or technology related uncertainty as well as product uncertainty). Moreover, Jones and Ostroy (1984) stress that the preserving of flexibility when faced with uncertainty is important for making decisions on whether to undertake irreversible investments. In the same vein, Tombak (1990) constructs a game-theoretic model to determine investments in FMS by firms competing in an oligopolistic market, whereas Roller and Tombak (1993) extend to a two-stage game in which firms choose between a flexible and a less flexible technology in the first stage followed by choosing production quantities in the second stage. With respect to the competitiveness role, as pointed out for example by Roller and Tombak (1991, 1993), high manufacturing flexibility of a particular firm can induce higher competitive pressure for its rivals, and increase profit margins for the relatively more flexible firm. Eaton and Schmitt (1994) further show that while flexibility leads to market concentration, the resulting equilibrium need not be welfare-dominated by one where firms are prohibited from merging, forming cartels, or engaging in market preemption. Concerning both views: Firms might "bank flexibility", that is holding flexibility in reserve to meet future needs. In this sense flexibility is an investment which creates future options for a company.

Different from the papers in this third line of literature we formally embed the concept of FMS in a generalized CES production function with endogenously determined production techniques. This specification in turn allows us to calibrate industry and firm-level production function parameters and run counterfactual policy experiments using a structural model consistent with firm-level data from manufacturing industries.

2 Motivational Evidence: (Distorted) Flexibility of Production and Performance

In order to motivate the interaction between flexibility of production and performance, in this section we provide evidence from the business literature for efficiency gains through flexibility while also delineating on the potential sources of inflexibility at the firm-level.

Generally speaking, in many manufacturing industries producers often receive demand orders after employing the production factors (such as materials, land, capital and labor). One such case is in the pharmaceuticals industry. For instance, flu vaccines and various inputs required to manufacture vaccines cannot be stored for longer periods. The demand for a particular type of flu serum is usually unpredictable and quite volatile with respect to year-to-year comparisons, asking for the capacity to efficiently use a variety of different input combinations when demand for vaccines arise. To highlight this point, at a public speech in 2007, Jeffrey Kindler – the former CEO of Pfizer – prioritized establishing a highly flexible production base as one of his company's key short-term targets.

There are other examples from manufacturing industries that promote the role of the micro-level flexibility on firm-level outcomes. For instance, Adler, Goldoftas and Levine (1999) study the effect of organizational flexibility on efficiency in the car-manufacturing industry. By providing detailed micro-level evidence from Toyota's NUMMI plant in California, authors document that company's policy changes that have led to increases in its labor input flexibility stimulated production efficiency at the beginning of 1990s, and gained Toyota a large competitive advantage over its big rivals Ford, Chrysler and General Motors.

In other innovation intensive industries – such as the high-tech IT manufacturing, flexible manufacturing is now the standard business practice. In the IT sector, it is often suggested that investment in technique flexibility is much more efficient than investment in ability to forecast demand fluctuations. Due to fast technological advancements IT products cannot be inventorized in large quantities for extended periods. In this sector, most of the success of manufacturers in Taiwan, Korea and Japan is credited to the operational flexibility of production lines and the induced efficiency in product quality and delivery rates (see Beach, Muhlemann, Price, Paterson and Sharp (2000)).

Empirical research that aims to evaluate the relationship between flexible production and firm-performance relies on surveys, case studies as well as formal econometric methods, which we delineate in the following.

2.1 Surveys

Using a manufacturing survey, administered by INSEAD, Boston University and Waseda University, on the manufacturing strategy of large manufacturers of Europe, Japan and North America, de Meyer, Nakane, Miller and Ferdows (1989) conclude that Japanese were ahead of their European and North American competitors in utilizing flexible manufacturing to cut costs through rapid production and design changes.

Using the manufacturing futures survey data in 1983-86 in Europe and in 1985 in North America, Tombak and de Meyer (1988) find that manufacturers in both Europe and North America use Flexible Manufacturing Systems for adapting to *input variations* rather than product design changes. Our technique-based modeling strategy is consistent with this finding.

Jaikumar (1986) conducts a focused study of 35 manufacturers in the U.S. and 60 in Japan, finding that on average American firms are more capital-biased whereas Japanese firms are more labor-biased when choosing their production processes. Finally, Cusumano, Fine and Suarez (1996) study 31 printed circuit board plants of 14 electronics firms in the U.S., Japan, and Europe and find out *complementary* relationships among different layers of production flexibility – and as to be seen below, our findings depend critically on the complementarities between industry- and firm-level production flexibilities.

2.2 Case Studies

There are numerous case studies in the business literature concerning the efficiency gains to be obtained through establishing flexible production processes. For brevity, we summarize only selectively the following cases:

1. Toyota: Womack, Jones and Roos (1990) point of the advantage of Toyota FMS to produce at the time needed and in the quantities needed to avoid unnecessary inventories and to reduce manufacturing costs significantly, thereby enabling it to outgrow Ford, Chrysler and General Motors.

2. Lincoln Electric Company (producing welding equipment): Milgrom and Roberts (1995) illustrate that a welding equipment producer, Lincoln Electric Company, had much better performed than peer-competitors due to its flexible work rules with cross-trained workers and cross-functional development teams, accompanied by strong promotion and employee bonus incentives, making General Electric eventually drop out of the welding equipment business.

3. UMC-Media Tek Integrated Circuits (IC) Design Company: In the (IC) industry the key competitiveness of Korea and Taiwan lies in the speed to implement and the flexibility in response to changes in market demand. Chang and Tsai (2002) argue that Taiwan enjoys a competence of a cheap but outstanding local design capability pool. By mobilizing such process flexibility, Taiwan adopts the strategy of being a rapid follower to provide quick IC design that is less expensive than what can be provided by most advanced countries, with quality much better than that delivered by other developing countries. Design for manufacturability, in this respect, emerges as a key concept to enhance productivity in a resource limited country such as Taiwan. To give a concrete example, in CD-ROM and DVD production Taiwan enjoyed a competitive advantage during 1990s thanks to its capacity to redesign quickly with respect to market changes. A key example was illustrated by Chang and Tsai (2002): UMC (United Microelectronic Co.), an IC company, converted its multimedia design department to form the Media Tek IC Design Company specialized in CD-ROM and DVD products. Based on its Design for Manufacturing capacity, the company was able to rapidly acquire the required techniques (within a period of less than a year) and launched the production of the CD-ROM chip. With world-wide-acceptable quality and at a very competitive price (compared to Japanese competitors), these CD-ROM chips quickly took up the global market share, peaking at 4-5 million chips of monthly output at the end of 1990s.

4. Schwabe Pharmaceuticals: In RolandBerger (2009) report, Dr. Rainer Oschmann, the Executive General Manager of Schwabe Pharmaceuticals, emphasizes the flexibility of their operational techniques as a clear strategic objective of his company.

5. Plastech: Berry and Cooper (1999) find that Plastech had drastic reduction in profitability when expanding product scope prematurely without suitable production flexibility.

6. Minnesota Manufacturers: Gerwin (1993) provides evidence that, as market unpredictability and competitiveness increase, Minnesota manufacturers become more flexible in their production processes to cut their manufacturing costs.

2.3 Econometric Analysis

Despite the abundance of survey and case studies, more systematic econometric analyses have been rare that concentrated on understanding the impact of flexibility on production efficiency. We list some exceptions in the following.

By conducting an empirical analysis on over 3000 companies from 83 industries over the period of 1979-87, Fiegenbaum and Karnani (1991) identified flexibility as a competitive advantage for small firms, as argued by Stigler (1939), especially in volatile and capital-intensive industries. Using a database of about 3,000 businesses, Roller and Tombak (1993) find that FMS plays an important role in *lowering the manufacturing cost*. The theoretical results that we will present below are consistent with this finding. In MacDuffie (1995), based on a 1989-90 survey of 62 auto firms, an increase in a production organization index (consisting of three subcomponents: skills and motivation for discretionary effort toward flexible production and integration of human resources with a flexible production system) is found to lower labor hours per vehicle and lead to higher productivity.

Ichniowski, Shaw and Prennushi (1997) use a panel data of 36 finishing lines of steel companies or mills in the U.S., finding that *flexible work rules*, such as flexible job design and training to provide workers with multiple skills, raise worker productivity far above those under more traditional rigid work practices. In his later piece, Ichniowski (1999) investigate 41 steel production lines from Japan and the U.S. and identifies significant productivity gains through flexible human resource management practices.

Finally, Ling-yee and Ogunmokun (2008) provide empirical evidence from a sample of 222 export product/market ventures, confirming that a firm's manufacturing flexibility enhances production performance.

Conclusion. The motivational evidence that we summarized in this section so far argues for that flexibility improves efficiency of production. In order to capture this key property of production processes, in our theoretical analysis we will incorporate firm- and industry-level flexibility concepts into an otherwise standard structural macro framework.

2.4 Motivating Distortions to Production Flexibility

Full-fledged flexibility might not be a virtue for every firm. How flexibly a firm can process the relative efficiency of its production techniques could be subject to within firm resistance, limited information concerning the interactions between factors of production and simply unintended mistakes.

In the Introduction, we highlight three sources of such mistakes in practice based on three key papers in the management science literature, namely, Fine and Freund (1990), Pailles, Yannou and Bocquet (1996) and, most relevantly, Siggelkow (2002). An important property established is that such mistakes arising from misperceptions with respect to production input activities are more costly when these activities are complements rather than substitutes (cf. Siggelkow (2003)). In a more recent paper, Ghemawat and Levinthal (2008) study strategies for achieving higher levels of performance and offsetting past mistakes through tactical adjustments. In justifying mistakes, they argue that "[g]rappling with interactions among choices poses challenges for decision makers" due to "the curse of dimensionality" (*à la* Bellman). They further elaborate "rich interactions among a large number of choices imply the nonexistence of a general, step-by-step algorithm that can locate the best set of choices in a "reasonable" period of time" (p. 1639).

In a follow-up study to Siggelkow (2002), Rivkin and Siggelkow (2003) examine interdependencies among a firm's vertical hierarchy, incentive system and limits on the ability of managers to process information and find that workforce incentives and managerial capabilities are complements to an active hierarchy when there are sufficiently pervasive interactions among production process decisions. Empirically, Jeffers, Muhamma and Nault (2008) investigate whether there exist complementarities between IT resources and non-IT resources at the production process level. They conclude: "For decision-makers, our findings demonstrate that the performance impact of IT resources is shaped and influenced by their interactions with other non-IT resources. ... Failure to recognize complementary interactions could lead to unnecessary overemphasis on certain categories of investment, whereas failure to take into consideration substitutive interactions could lead to a failure to address redundancies that may dampen the anticipated net impact of some investments" (p. 7). Based on survey data of the retail industry in the U.S., Powell and Dent-Micallef (1997) find that IT alone does not explain firms' performance variation, but that their ability to combine explicit IT technology resources with complementary human and business resources gives advantages over the competitors.

In our theoretical analysis, we will capture distorted flexibility of production by incorporating *ex post* mistakes into the technique decision making process of the firm by allowing the degree of technique-distortions to vary across firms. We will then indirectly back-out these distortions by exploiting the structure of the model with firm-level data. In a Handbook Chapter, Brynjolfsson and Milgrom (2013) emphasize that understanding complementary practices may shed light on whether "organizational complements to new technologies [may] explain changes in productivity growth across geography, time, and industry" and suggest that "[u]se of novel metrics of activity and performance, such as fine-grained, practice-specific inputs and outputs" may be a fruitful area for economists to investigate in order to advance our understanding with respect to the role of production complementarities played in "valuing the organizational capital and other intangible assets of firms" (Section 5.2: An Agenda for Economists). Our paper therefore addresses in part potential research avenues proposed by Brynjolfsson and Milgrom (2013).

3 A Benchmark Production Function with Techniques Choice

The benchmark economy features a representative firm, manufacturing a product with two factor inputs, capital and labor. Different from the neoclassical production framework, we augment raw measures of factor inputs with a combination of production techniques that serves to organize the factor inputs in an effective manner in order to enhance the performance of the production process. Importantly, the production-techniques combination is a firm-level control variable, which is to be chosen from a firm-specific technology menu. For the time being, we assume that there are no distortions associated with production factor inputs or the choice of production techniques. Also, in this section we focus solely on firm's production structure – by leaving the details to the end of demand structure and production distortions to Section 4.

3.1 The Basic Environment

Let us denote capital with K and labor with L. The *combination of production techniques* is captured by a pair (a_K, a_L) which augment the two factor inputs (K, L) to govern their usage and coordinate their match. The concept of production techniques is in line with the literature on the property of the firm and the aggregate production function developed by Houthakker (1955-1956), Kortum (1997) and Jones (2005). It also captures factor-augmenting technology improvement modeled by Caselli (1999), Acemoglu (2003), and Caselli and Coleman (2006). In this respect, one may also rename a_K and a_L, respectively, as capital-augmenting and labor-augmenting techniques. The aim of this paper is to understand the aggregate consequences of inflexible production design through technique-choice distortions and to compare the qualitative as well as quantitative implications of technique-distortions against those of factor and output distortions.

Our framework follows the above mentioned Houthakker-Kortum-Jones literature – on the shape of aggregate production function – by assuming that the availability of techniques is subject to a technology constraint

$$H(a_K, a_L) = z, \quad (1)$$

$$a_K \geq \underline{a}_K > 0, \quad (2)$$

$$a_L \geq \underline{a}_L > 0, \quad (3)$$

where z is the *firm-specific technology frontier*. The firm is said to be more *efficient* in the process of production if it has a higher level of z. Together with the chosen techniques combination, the technology-frontier specifies firm's physical total factor productivity.[6] The parameters $\underline{a}_K$ and $\underline{a}_L$ are *industry-specific* limit production-techniques, which allow the unit cost-function to be well-behaved at the boundaries.

Throughout the paper, we will assume that $H(a_K, a_L) = a_K^{\alpha} a_L^{1-\alpha}$. This technology constraint specifies the *full menu* of production techniques – describing the extent of trade-off across different combinations of (a_K, a_L) under a given technology frontier z. The trade-off associated with techniques is qualitatively similar to the concept of iso-quant, which can be referred as the *iso-tech*.

We then depart from Houthakker-Kortum-Jones where a Cobb-Douglas "global" production function can be derived as an envelope of the Leontief "local" production function with techniques drawn from an independent Pareto distribution. We instead assume that the representative firm's

[6] With (a_K, a_L) and the associated knowledge level z, there is no need to add another scaling parameter to the production function.

production function takes the Constant Elasticity Substitution (CES) form

$$Y = [\lambda(a_K K)^\rho + (1-\lambda)(a_L L)^\rho]^{\frac{1}{\rho}}.$$

The parameter $\rho \in (-\infty, 1]$ is industry-specific and it captures the flexibility of the production technology in allowing the firm to substitute between the technique-augmented factor inputs, $a_K K$ and $a_L L$, with $1/(1-\rho)$ measuring the elasticity of substitution. The parameter λ is thus the effective capital share of production.

3.2 Firm's Optimization

The representative firm optimizes by choosing a combination of production techniques and production factors. In this respect, the production is a two-staged process: (i) in **Step 1**, the firm chooses a suitable combination of production techniques from the technology menu to ensure the full efficiency of the production process; and (ii) in **Step 2**, the firm decides on the quantities of capital and labor to achieve a given level of output. While Step 2 is the standard optimization under the neoclassical production framework, Step 1 is the techniques choice problem. We solve for the optimal techniques-combination and optimal factor demands backward: at first we solve for the optimal K and L of the firm by taking factor prices and production techniques (a_K, a_L) as given; we then determine the optimal (a_K, a_L) combination.

Specifically, the firm in **Step 2** solves the following cost minimization problem

$$\begin{aligned} \min_{K,L} \quad & rK + wL \\ s.t. \quad & [\lambda(a_K K)^\rho + (1-\lambda)(a_L L)^\rho]^{\frac{1}{\rho}} = Y. \end{aligned} \tag{4}$$

The solution to the neoclassical cost minimization yields a unit cost function conditional on a particular pair of production techniques, $\tilde{c}(a_K, a_L; r, w)$.

In **Step 1**, the firm pins down techniques choice to achieve the lowest unit cost of production under a given techniques menu

$$\begin{aligned} \min_{a_K, a_L} \quad & \tilde{c}(a_K, a_L; r, w) \\ s.t. \quad & H(a_K, a_L) = z. \end{aligned} \tag{5}$$

Throughout the paper we will refer to Step 1 program as *techniques choice* and Step 2 program as neoclassical *cost minimization.*

3.2.1 Neoclassical Cost Minimization

We start by solving the neoclassical cost-minimization problem. Throughout the paper, we shall relegate all detailed mathematical derivations and proofs to the Appendix. The first-order conditions from the neoclassical cost minimization yields

$$\frac{K}{L} = \left(\frac{w}{r}\right)^{\frac{1}{1-\rho}} \left(\frac{\lambda}{1-\lambda}\right)^{\frac{1}{1-\rho}} \left(\frac{a_K}{a_L}\right)^{\frac{\rho}{1-\rho}}. \tag{6}$$

Thus, the capital-labor ratio is inversely related to the factor price ratio, which is standard. How the capital-labor ratio responds to the techniques ratio depends crucially on the industry-level production flexibility. When the two technique-augmented factor inputs are *Pareto complements* ($\rho < 0$), the capital-labor ratio is negatively related to the techniques ratio. This is quite intuitive: under Pareto complementarity, it is profitable to balance between the two technique-augmented factor inputs. In this case, if the organization of factor inputs is biased towards one particular factor, then it is expected that the firm would employ more of another factor to ensure balanced factor usage. When the two technique-augmented factor inputs are *Pareto substitutes* ($0 < \rho < 1$), the opposite is true: the firm employs more of the input associated with a better technique.

The unit cost function resulting from the neoclassical cost minimization is a function of production techniques (a_K, a_L)

$$\tilde{c}(a_K, a_L; r, w) = \left[\left(\frac{r}{a_K}\right)^{\frac{\rho}{\rho-1}} \lambda^{\frac{1}{1-\rho}} + \left(\frac{w}{a_L}\right)^{\frac{\rho}{\rho-1}} (1-\lambda)^{\frac{1}{1-\rho}}\right]^{\frac{\rho-1}{\rho}}. \tag{7}$$

This equation indicates that the unit cost of production is a CES aggregator of the technique-deflated factor costs. The endogenous adjustments in production techniques are the key to differentiate this unit cost function from the standard neoclassical one, to which we shall turn.

3.2.2 Techniques Choice

When solving for the optimal techniques combination we need to keep in mind that both interior and corner solutions are possible. We define an interior solution as follows.

Definition (Interior Techniques Choice) Denoting the optimal techniques combination that minimizes the unit cost of production with (a_K^*, a_L^*), (a_K^*, a_L^*) is an interior solution to the techniques choice problem if and only if $a_K^* \neq \underline{a}_K$ and $a_L^* \neq \underline{a}_L$.

At first we characterize the interior solution to techniques choice program. After deriving the unit cost of production we will also characterize the parameter constellations of the model that induce the interior solution to be optimal. The interior solution to techniques choice problem gives

$$\frac{a_K^*}{a_L^*} = \frac{r}{w} \left(\frac{1-\lambda}{\lambda}\right)^{\frac{1}{\rho}} \left(\frac{1-\alpha}{\alpha}\right)^{\frac{\rho-1}{\rho}}, \tag{8}$$

which depends positively on the factor price ratio. Intuitively, when a factor input becomes pricier, it is profitable to devote more effort toward enhancing the technique associated with that particular factor in order to minimize the neoclassical unit cost.

Plugging (8) in (6) solves for the capital-labor ratio of

$$\frac{K}{L} = \frac{w}{r}\frac{\alpha}{1-\alpha}. \tag{9}$$

While the optimized capital-labor ratio induced by the interior techniques-combination continues to be inversely related to the factor price ratio, the factor cost share $\frac{rK}{wL}$ turns out to be a constant. Furthermore, the K/L ratio depends only on the relative shares in the technology menu, $\frac{\alpha}{1-\alpha}$, and not on the relative relative share of efficient units of capital and labor in the production function, $\frac{\lambda}{1-\lambda}$.

In order to determine the *levels* of production techniques dictated by the interior solution, we combine (8) with (1) to derive:

$$a_K^* = z\left(\frac{w}{r}\right)^{-(1-\alpha)}\left(\frac{\alpha}{1-\alpha}\right)^{(1-\alpha)\left(\frac{1-\rho}{\rho}\right)}\left(\frac{1-\lambda}{\lambda}\right)^{(1-\alpha)\left(\frac{1}{\rho}\right)} > \underline{a}_K, \tag{10}$$

$$a_L^* = z\left(\frac{w}{r}\right)^{\alpha}\left(\frac{\alpha}{1-\alpha}\right)^{-\alpha\left(\frac{1-\rho}{\rho}\right)}\left(\frac{1-\lambda}{\lambda}\right)^{-\alpha\left(\frac{1}{\rho}\right)} > \underline{a}_L. \tag{11}$$

Intuitively, both techniques are linear in the level of technology-frontier. Moreover, they depend on the factor price ratio rather than the individual factor prices: a higher wage-rental ratio induces techniques combination to be more biased towards labor. Importantly, industry-level production flexibility affects the choice of techniques through the share of factor incomes and the share of techniques in the technology menu. Next we turn to analyzing the properties of the unit cost of production and derive the parameter conditions of the model that promote the interior (a_K^*, a_L^*)-solution to be optimal.

3.3 Unit Cost of Production

By combining the optimal techniques choice with the neoclassical cost expression that we derived at (7), we can solve for the unit cost of production implied by our framework:

$$c(w,r) = \frac{1}{z}\left(\left(\frac{\alpha}{\lambda}\right)^{\frac{1}{\rho}}\frac{r}{\alpha}\right)^{\alpha}\left(\left(\frac{1-\alpha}{1-\lambda}\right)^{\frac{1}{\rho}}\frac{w}{1-\alpha}\right)^{1-\alpha}. \tag{12}$$

This final form of unit cost allows us to obtain the following important result.

Proposition 3.1 *(Optimality of the Interior Techniques Choice) For $\rho \in (-\infty, 0)$, the interior-solution for the techniques-choice, (a_K^*, a_L^*), minimizes the unit cost of production. For the case of $\rho \in (0, 1]$, the optimal techniques-choice is a corner.*

Proof *All proofs are relegated to the Appendix.*

Figure 1 illustrates the interior solution as an optimal choice of production techniques. As we will delineate in Section 7, for all manufacturing industries that we focus on in this study, empirical estimates from the literature show that the condition $\rho < 0$ holds. Therefore, in the remainder of the theoretical as well as quantitative analysis we solely concentrate on the case of $\rho < 0$ when deriving and evaluating the properties of our framework.

Having derived the parameter condition that supports the interior solution to be optimal, we move on and analyze further properties of the unit cost of production, that we derived at (12). We first note a standard property of the unit cost function: A rise in technology frontier (higher z) reduces the unit cost of production.

Interestingly, while the conditional unit cost function (that we derived at (7)) is a CES aggregator of factor prices, the final form of the unit cost function, after taking into account the optimal techniques choice, becomes a Cobb-Douglas aggregator of factor prices weighted by technique usage rather than factor income shares. Moreover, this Cobb-Douglas aggregator depends on the ratios of technique usage to factor income shares, $\frac{\alpha}{\lambda}$ and $\frac{1-\alpha}{1-\lambda}$, and production flexibility ρ.

Finally, we turn to studying the implications of (industry-level) production flexibility for the unit cost of production. To begin, using (12) we establish the following limit properties. In the limit cases, with extreme flexibility, when $\rho \to -\infty$ the unit cost converges to

$$c(w,r) = \frac{1}{z}\left(\frac{r}{\alpha}\right)^{\alpha}\left(\frac{w}{1-\alpha}\right)^{1-\alpha},$$

whereas when $\rho \to 1$, the unit cost cost converges to

$$c(w,r) = \frac{1}{z}\left(\frac{r}{\lambda}\right)^{\alpha}\left(\frac{w}{1-\lambda}\right)^{1-\alpha}.$$

Thus, while the factor prices are always weighted by technique usage shares, how much they affect the unit cost depends crucially on production flexibility. When industry flexibility is shut down ($\rho \to -\infty$), or in other words efficient factors are perfect complements, the production technology (the CES aggregator) precludes technique-augmented factor inputs from substituting each other. As a result, factor prices are deflated only by their technique usage shares. With a greater technique usage share, a factor price would not raise the unit cost of production as much. When flexibility is perfect, on the contrary, factor prices are deflated only by their income shares. In this case, an increase in the price of a factor with a greater income share would become less damaging to the unit cost of production.

With the extreme cases addressed, in the next proposition we present what happens with intermediate levels of flexibility.

Proposition 3.2 *(Production Flexibility and Unit Cost) Industry's production flexibility (ρ) monotonically reduces the unit cost of production for any given pair of factor prices.*

Proposition 3.2 indicates a positive effect of aggregate production flexibility on firm performance. This result echoes an extensive list of findings highlighted in the management science literature, such as Roller and Tombak (1993), Gerwin (1993) and Adler, Goldoftas and Levine (1999), all of whom argue that overall production flexibility is an important determinant of efficiency.

In the next section, we introduce distortions into our benchmark model and investigate the interactions between industry-level production flexibility and distortions originating from factor, output and most importantly from technique decisions of the firm.

4 Capital, Output and Technique Distortions

Distortions to firms' factor inputs and output and their aggregate implications for misallocation have been extensively analyzed in the literature. In this section we introduce a novel form of distortion emerging from firms' technique decisions and formalize a foundation to conduct aggregation exercises with factor, output and technique distortions. For this purpose, we extend the specification of Section 3 to incorporate a demand structure to the benchmark model and importantly to also allow for distortions in firms' production decision margins. The full-fledged decision program of the firm is summarized as follows – with details of each stage to be described thereafter.

$$\begin{aligned}
\text{Stage 1} \quad & \max_{a_K, a_L} \; Y = [\lambda(a_K K)^\rho + (1-\lambda)(a_L L)^\rho]^{\frac{1}{\rho}} && (13)\\
s.t. \quad & a_K^\alpha a_L^{1-\alpha} = z, \\
& a_K \geq \underline{a}_K > 0, \\
& a_L \geq \underline{a}_L > 0, \\
\text{Stage 2} \quad & \text{Nature chooses a technique distortion } \phi \\
\text{Stage 3} \quad & \min_{K,L} \; r(1+\eta_K)K + wL, && (14)\\
s.t. \quad & Y = [\lambda(a_K K)^\rho + (1-\lambda)(a_L L)^\rho]^{\frac{1}{\rho}}, \\
\text{Stage 4} \quad & \max_{p} \; (1-\eta_Y)pY^d(p) - c(\phi,\eta)Y^d(p), && (15)\\
s.t. \quad & Y^d(p) = \left(\frac{p}{P}\right)^{-\sigma} Y_J.
\end{aligned}$$

Stages 1 and 2 capture firm-level techniques choice with distortions, where the distortion to techniques-choice combination is firm-specific and is denoted with ϕ, whose origins are to be delineated below. Stage 3 is the factor choice with distortions, where we introduce the firm-specific factor distortion without loss of generality from the side of capital and denote it with η_K. Stage 4 is the final decision-making stage in which, the firm decides on its unit output price p, by taking the demand structure, aggregate industry price-level (P) and industry-level output (Y_J) as given in order to maximize its profits. We assume that the firm's profit maximization program is subject idiosyncratic distortions as well, which we call as output distortions, denoted with η_Y. We assume that η_K and η_Y are known in Stage 1. However, allowing uncertainty for η_K and η_Y would not necessarily impact qualitative and quantitative findings. Throughout the theoretical analysis we maintain the following structural assumption.

Assumption 1. $\rho \in (-\infty, 0)$.

Based on this key assumption – which we will justify in Section 7, we again solve recursively by starting from the output pricing decision.

4.1 Demand and Output Distortion

We assume that firms are monopolistic competitors a la Dixit-Stiglitz with a demand structure as specified at (15). Given the output distortion η_Y and the demand specification, the unit price of output is expressed as

$$p = \frac{\sigma}{\sigma - 1} \frac{c(w, r; \eta_K, \phi)}{1 - \eta_Y}, \tag{16}$$

with a prevailing firm-level profit of

$$\pi = \left(\frac{\sigma}{\sigma - 1}\right)^{\sigma} (\sigma - 1)^{-1} c(r, w; \eta_K, \phi)^{1-\sigma} Y_J. \tag{17}$$

4.2 Capital Distortion

We assume that the cost of capital exhibits a firm-specific friction. A capital cost friction can prevail from capital market imperfections as well as capital taxes, as widely discussed in the misallocation literature. This component can be conveniently expressed as $r(1 + \eta_K)$, where η_K can take positive as well as negative values. Positive values of η_K imply the "taxation of capital", whereas negative values of η_K mean "subsidization" (in a broader sense). In our quantitative analysis we will back out a distribution of "taxes" and "subsidies" across firms using firm-level data.

Taking firm-specific capital distortion into account, neoclassical cost minimization yields

$$\frac{K}{L} = \left(\frac{w}{r(1 + \eta_K)}\right)^{\frac{1}{1-\rho}} \left(\frac{\lambda}{1 - \lambda}\right)^{\frac{1}{1-\rho}} \left(\frac{a_K}{a_L}\right)^{\frac{\rho}{1-\rho}}, \tag{18}$$

and the conditional unit cost of production becomes

$$\tilde{c}(a_K, a_L; r, w) = \left[\left(\frac{r(1 + \eta_K)}{a_K}\right)^{\frac{\rho}{\rho-1}} \lambda^{\frac{1}{1-\rho}} + \left(\frac{w}{a_L}\right)^{\frac{\rho}{\rho-1}} (1 - \lambda)^{\frac{1}{1-\rho}}\right]^{\frac{\rho-1}{\rho}}. \tag{19}$$

Applying comparative statics at (19) shows that for a given pair of techniques (a_K, a_L), the unit cost of production rises as the capital distortion (η_K) increases. Not surprisingly, capital distortions result in a higher capital user cost, which in turn increases the unit cost of production.

4.3 Techniques Choice with Distortions

Techniques choice is subject to distortions that are unforeseeable as of Stage 1. This means after a techniques combination is chosen in Stage-1, such as (a_K^*, a_L^*), the firm realizes in Stage-2 that it made a *mistake* when choosing techniques, such that its operational capital-technique will turn out to be $\hat{a}_K = a_K^*(1+\phi)$, with $\phi \in (-1, \bar{\phi}]$ and $\bar{\phi} > 0$, instead of a_K^*.[7] Despite the fact that techniques combination of the firm gets distorted from an optimal benchmark, the firm will continue to operate on the same technology frontier, determined by z, as we depict in Figures 2 and 3.

In our framework, the notion of "technique mistakes" is broadly defined in order to capture a spectrum of different sources of (in)flexible techniques decision-making at the firm-level. As we highlighted in the Introduction and in Section 2, limited flexibility can prevail for various reasons. For instance, when establishing the blue-print of a firm, the manager might need to work with limited information about how factors of production will interact with each other when the foundation of the unique business-plan is in place. This can generate ample room for misperceptions in techniques decision-making to play a role and distort technique-outcomes from an optimal benchmark as discussed by Siggelkow (2002) in a related context. Another dimension of technique distortions may arise if the ownership and the manager of a business are separated from each other and the manager is in charge of technique decisions. In such situations, although the ownership intends to observe a particular optimal techniques-combination *ex ante* (a_K^*, a_L^*), it might end up with a distorted one *ex post* $(\hat{a}_K, \hat{a}_L)$ because of managerial resistance to not deviate from a particular techniques-combination and to bias the efficiency of a particular factor, as deliberated in Fine and Freund (1990) and Pailles, Yannou and Bocquet (1996). Finally, the manager of the firm could also make unintended errors when establishing the blue-print of a unique business-plan and generate distortions in production techniques compared to a desired optimal benchmark. We model these limits to flexible techniques-choice as unforeseeable mistakes (so by construction $E[\phi] = 0$).

The structural assumptions that govern the technique-mistakes yield then an effective $(\hat{a}_K,\hat{a}_L)$ combination for the firm denoted as

$$\hat{a}_K = (1+\phi)^{1-\alpha} a_K^*, \tag{20}$$

$$\hat{a}_L = (1+\phi)^{-\alpha} a_L^*, \tag{21}$$

where

$$a_K^* = z\left(\frac{w}{r(1+\eta_K)}\right)^{-(1-\alpha)} \left(\frac{\alpha}{1-\alpha}\right)^{(1-\alpha)\left(\frac{1-\rho}{\rho}\right)} \left(\frac{1-\lambda}{\lambda}\right)^{(1-\alpha)\left(\frac{1}{\rho}\right)},$$

$$a_L^* = z\left(\frac{w}{r(1+\eta_K)}\right)^{\alpha} \left(\frac{\alpha}{1-\alpha}\right)^{-\alpha\left(\frac{1-\rho}{\rho}\right)} \left(\frac{1-\lambda}{\lambda}\right)^{-\alpha\left(\frac{1}{\rho}\right)},$$

[7] The upper bound $\bar{\phi}$ is needed when proving Proposition 4.1(iii-b) particularly for the case of $\rho < 0$ and $\phi > 0$.

and hence

$$\frac{\hat{a}_K}{\hat{a}_L} = \frac{r(1+\eta_K)}{w}\left(\frac{1-\lambda}{\lambda}\right)^{\frac{1}{\rho}}\left(\frac{1-\alpha}{\alpha}\right)^{\frac{\rho-1}{\rho}}(1+\phi). \tag{22}$$

Firm's operational techniques-ratio reveals that lowering η_K and ϕ induce techniques combination to be biased toward labor-augmenting regardless of the elasticity of substitution between technique-augmented factor inputs. Plugging the *distorted* techniques-combination ($\hat{a}_K$,$\hat{a}_L$) in (18) provides

$$\frac{K}{L} = \frac{w}{r}\frac{\alpha}{1-\alpha}\frac{(1+\phi)^{\frac{\rho}{1-\rho}}}{1+\eta_K}, \tag{23}$$

with

$$K = c(r,w;\phi,\eta_K)^{\frac{1}{1-\rho}}\left[r(1+\eta_K)\right]^{-\frac{1}{\rho}}\lambda^{\frac{1}{1-\rho}}\hat{a}_K^{\frac{\rho}{1-\rho}}Y^d(p), \tag{24}$$

$$L = c(r,w;\phi,\eta_K)^{\frac{1}{1-\rho}}w^{\frac{-1}{1-\rho}}(1-\lambda)^{\frac{1}{1-\rho}}\hat{a}_L^{\frac{\rho}{1-\rho}}Y^d(p). \tag{25}$$

The expression we obtained for the K/L ratio at (23) implies that for $\rho < 0$ and $\phi > 0$, an increase in ϕ lowers the K/L ratio of the firm, as such mistakes distort the decision on capital-techniques.

4.4 Unit Cost with Distortions

The unit cost of production with both capital and technique distortions is expressed as follows

$$c(r,w;\phi,\eta_K) = \frac{(1+\phi)^{\alpha}}{z}\left[\left(\frac{\alpha}{\lambda}\right)^{\frac{1}{\rho}}\frac{r(1+\eta_K)}{\alpha}\right]^{\alpha}\left[\left(\frac{1\text{-}\alpha}{1\text{-}\lambda}\right)^{\frac{1}{\rho}}\frac{w}{1\text{-}\alpha}\right]^{1-\alpha}\left[1+\alpha\left((1+\phi)^{\frac{\rho}{1-\rho}}-1\right)\right]^{\frac{\rho-1}{\rho}}, \tag{26}$$

whose full derivation can be found in the Appendix. An increase in capital distortion (η_K) raises the unit cost of production. Evaluating the effect of ϕ on the unit cost function shows that at $\phi^* = 0$ the unit cost of production reaches a global minimum, which is true as long as Assumption 1 holds. Hence both positive and negative distortionary deviations from optimal techniques are undesirable. The intuition for technique-distortions to raise unit cost is that an inefficient combination of techniques induces the firm to operate along a higher iso-cost curve as we illustrate in Figure 3. This conclusion confirms the findings that we referred in the Introduction and in Section 2: Flexible decision making is a highly desirable asset to improve firm-level outcomes and limitations to it (which we capture with technique distortions) can cause efficiency losses. Our model captures this important property, whose aggregate implications we will investigate in Section 7.

An important component of flexibility stems from the industry. In other words, industry-level production flexibility gives rise to the extent to choose efficient factors flexibly. The next question to be addressed becomes then whether the distortionary effects of the capital and technique frictions on the unit cost of production are influenced by the industry-level production flexibility, ρ. We also inquire whether capital and technique distortions reinforce each other when determining the unit cost of production. We are basically interested in signing $\frac{\partial^2 c}{\partial\phi\partial\rho}$ and $\frac{\partial^2 c}{\partial\phi\partial\eta_K}$. The following proposition provides the key properties of the unit cost of production to this end – with details of the comparative statics to be found in the Appendix.

Proposition 4.1 *(Production Flexibility, Distortions and Unit Cost of Production)*

(i) *Increasing the capital cost distortion or deviating with the technique distortion from* $\phi^* = 0$ *raises the unit cost of production.*

(ii) *Production flexibility does not mitigate the detrimental effects of capital distortions on the unit cost of production.*

(iii) a. *if* $\frac{1}{\alpha}\frac{\rho}{\rho-1} > 1$*, production flexibility mitigates the distortionary effects of* $|\phi|$ *on unit cost;*

b. *if* $\frac{1}{\alpha}\frac{\rho}{\rho-1} < 1$*, production flexibility mitigates the distortionary effects of* $|\phi|$ *on unit cost if*

$$1 + \phi < \bar{\phi} \equiv \frac{1}{\left(1 - \frac{1}{\alpha}\frac{\rho}{\rho-1}\right)^{\frac{\rho-1}{\rho}}}; \tag{27}$$

(iv) *The detrimental effects of capital and technique distortions on the unit cost of production reinforce each other.*

We would like to note that the quantitative properties of the framework that we analyze in Section 7 will satisfy the sufficient condition (27) – promoting industry-level production flexibility as a mitigating factor of technique distortions. The intuition for this property is the following: when ρ is low, then the technique-augmented factors turn out to be complements and dismissing this strong interaction between factors (and sub-optimally biasing one factor) becomes costly. When ρ is high, the technique-augmented factors are substitutes and do not exhibit a strong interaction with each other, under which case dismissing this weak interaction (and biasing one factor) does not cause large efficiency losses. This result and the underlying intuition echoes Siggelkow (2002), who in a related context using very different modeling strategy argues that in early-stage decision making process of a business, misperceiving the interactions between complements would be much more distortionary for the performance of the business than misperceiving the interactions between substitutes.

5 Empirical Justification for the Theoretical Structure

Is there an empirically testable prediction that one can derive based on the structure of our model to confront with data? In order to address this question we make the following observations regarding the structural implications of η_K, η_Y and ϕ distortions. First,

$$\frac{K}{L} = \frac{w}{r}\frac{\alpha}{1-\alpha} \cdot \underbrace{\frac{(1+\phi)^{\frac{\rho}{1-\rho}}}{1+\eta_K}}_{\equiv \frac{1}{1+\tau_K}}, \tag{28}$$

which means that capital-labor ratio is a function of a (structural) endogenous wedge, denoted with τ_K, which in turn is a function of η_K and ϕ. Second, defining $\Sigma(\phi) \equiv \left[1 + \alpha\left((1+\phi)^{\frac{\rho}{1-\rho}} - 1\right)\right]^{\frac{\rho-1}{\rho}}$, the ratio between the total cost of labor and the total revenues of a firm can be expressed as

$$\begin{aligned} \frac{wL}{pY} &= \frac{c(r,w;\phi,\eta_K)^{\frac{1}{1-\rho}} w^{\frac{-1}{1-\rho}} w(1-\lambda)^{\frac{1}{1-\rho}} (\hat{a}_L)^{\frac{\rho}{1-\rho}} Y}{\frac{\sigma}{\sigma-1} c(r,w;\phi,\eta_K) Y} \\ &= \left(\frac{\sigma-1}{\sigma}\right)(1-\alpha) \cdot \underbrace{\left(\frac{1}{\Sigma(\phi)}\right)^{\frac{\rho}{\rho-1}} (1-\eta_Y)}_{=1-\tau_Y}. \end{aligned} \tag{29}$$

Hence, the ratio between the total cost of labor and revenues yields another structural wedge as a function of η_Y and ϕ, which we denote with τ_Y. Applying comparative statics at τ_K and τ_Y – as defined in equations (28) and (29) – shows that

$$\frac{\partial \tau_K}{\partial \phi} > 0, \frac{\partial \tau_Y}{\partial \phi} < 0.$$

This means τ_K and τ_Y would be negatively correlated among a cross-section of firms, if firms face distortions to optimal production techniques. This is a testable prediction of our model.

In order to confront this key prediction of the model with data, we conduct an empirical analysis using Compustat North America – a database, which we will also utilize in our quantitative analysis in Section 7. In our empirical analysis we focus on the manufacturing industry clusters that we list Table 1. We back out τ_K and τ_Y using firm-level values on capital, total labor expenditures and revenues, and aggregate estimates on α and σ. We estimate α at the level of each industry using U.S. NBER Productivity Database and present the estimates of α in Table 2. We set $\sigma = 3$ as in Hsieh and Klenow (2009). Then, using estimates of α and $\sigma = 3$ in (28) and (29) we recover τ_K and τ_Y, whose distributional properties we present in Tables 3a and 3b.

We estimate the following regression model

$$\tau_{Y,it} = \beta_0 + \beta_1 \tau_{K,it} + \gamma \boldsymbol{X_{it}} + \mu_j + \theta_t, \tag{30}$$

where $\boldsymbol{X_i}$ is a vector of firm-level control variables (containing R&D expenditures, Total Assets, Intangible Assets, Earnings Retention, Long-term Debt and Profits – all scaled by the number of employees) and μ_j and θ_t are, respectively, 4-digit-industry- and time-fixed effects. The time-span of our analysis is 1995-2014. Firm-level control variables and industry- and time-fixed effects are included to capture other factors and unobserved heterogeneities that are not addressed in our framework. In the regression analysis we impose $\tau_Y < 1$ and $\tau_K < 50$ in order to control for outlier effects.[8]

[8]To give an example, for instance, it can be the case that R&D intensive firms receive subsidies from the government based on their output.

We present estimation results for the regression specification (30) in Table 4. After controlling for a variety of firm-level controls and industry and time fixed-effects, the regression result shows that the correlation between τ_K and τ_Y is negative and it is statistically significant at 1% level – providing an indirect – but an important – empirical basis for the validity of our theoretical structure.

6 Identification, Firm-level Productivity and Aggregation

In this section we present the identification of firm-specific distortions (η_K, η_Y, ϕ) and the technology-frontier (z) using firm-level data and the measurement of firm-level physical and revenue productivities (TFPQ and TFPR), aggregating which we will then also develop industry-level measures of total factor productivity (TFP).

6.1 Identifying Distortions

The steps that allow the identification of firm-specific distortions are as follows:

1. We utilize estimates for industry-level production flexibility, ρ, from Oberfield and Raval (2014) and Raval (2015), who quantify production flexibility parameters using a Generalized Constant Elasticity of Substitution production function across 4-digit manufacturing industry-clusters of the US economy. Estimates of ρ are provided in Table 2. As we present in Table 2, among manufacturing industries, estimates of ρ are found to take negative values, inducing the interior techniques choice that we derived in Section 3 as the unique optimal solution for all firms that we will cover in our data.

2. As described in the previous section, we estimate α at the level of each industry using U.S. NBER Productivity Database (Table 2).

3. We apply the identification steps also utilized by Hsieh and Klenow (2009) and

   a. assume $\sigma = 3$ and $r = 1.1$,

   b. and normalize $\kappa_J \equiv (P^\sigma Y_J)^{-\frac{1}{\sigma-1}} = 1$.

Then using firm-level observables on total cost of capital (TC), total labor expenditures (wL), total revenues (TR), capital (K) and the industry-level structural parameters we uniquely identify η_K, η_Y and ϕ. Specifically, the sum of total cost of capital and the total cost of labor gives us a total cost (TC) figure. Using, TC and TR in (16) provides the output distortion as

$$TR = pY = \frac{\sigma}{\sigma-1}\frac{c(r, w; \phi, \eta_K)Y}{(1-\eta_Y)} = \frac{\sigma}{\sigma-1}\frac{TC}{(1-\eta_Y)},$$

or, after simplification,

$$1-\eta_Y=\frac{\sigma}{\sigma-1}\frac{TC}{pY}\equiv\frac{\sigma}{\sigma-1}\frac{TC}{TR}. \tag{31}$$

We then recall from (29) that

$$(1+\phi)=\left\{\frac{1-\alpha}{\alpha}\left[\left(\frac{\sigma-1}{\sigma}\right)(1-\eta_Y)\frac{pY}{wL}-1\right]\right\}^{\frac{1-\rho}{\rho}}. \tag{32}$$

Using (31), wL, and TC in (32) identifies the technique distortion:

$$(1+\phi)=\left\{\frac{1-\alpha}{\alpha}\left[\frac{TC}{wL}-1\right]\right\}^{\frac{1-\rho}{\rho}}. \tag{33}$$

Finally, using (33), TC, wL and K in (23), we back out the capital distortion:

$$1+\eta_K=\frac{1}{rK}(TC-wL). \tag{34}$$

Therefore, three independent structural relations - by using information on TC/TR, TC/wL and $(TC-wL)/K$ - separately and uniquely identify each of (η_K,η_Y,ϕ). Finally, using $\kappa_J=1$ in the demand equation as in Hsieh and Klenow (2009) we identify an augmented measure of $\hat{z}$ as:

$$\hat{z}\equiv z\left[\lambda^{\alpha}(1-\lambda)^{1-\alpha}\right]^{\frac{1}{\rho}}=\frac{(pY^d)^{\frac{\sigma}{\sigma-1}}}{\left[(\gamma_K(\eta_K,\phi)K)^{\rho}+(\gamma_L(\eta_K,\phi)L)^{\rho}\right]^{\frac{1}{\rho}}}, \tag{35}$$

where

$$\begin{aligned}\gamma_K &\equiv \left(\frac{w}{r(1+\eta_K)}\right)^{-(1-\alpha)}\left(\frac{\alpha}{1-\alpha}\right)^{(1-\alpha)\left(\frac{1-\rho}{\rho}\right)}(1+\phi)^{1-\alpha},\\ \gamma_L &\equiv \left(\frac{w}{r(1+\eta_K)}\right)^{\alpha}\left(\frac{\alpha}{1-\alpha}\right)^{-\alpha\left(\frac{1-\rho}{\rho}\right)}(1+\phi)^{-\alpha}.\end{aligned}$$

As an important conclusion of these identification steps, we stress that we did not need to assign a value for λ to recover firm-specific distortions and the technology-frontier of the firm.

6.2 Firm-level Total Factor Productivity

We are now ready to use η_K, η_Y, ϕ and $\hat{z}$ to develop measures of firm-level productivity. To establish an industry-level measure of TFP, at first we need to define firm-level physical and revenue productivities (TFPQ and TFPR). We work with two alternative measures of TFPQ, based on which we then also measure TFPR under two alternatives.

In our first TFPQ measure (which we will refer as TFPQ1), we suppose that the firm – instead of being exposed to the staged-decision making process that we analyzed so far – starts out with a TFPQ such that when it solves the neoclassical cost minimization problem it ends up with the unit cost function that we expressed at (26). Specifically, we solve for TFPQ1 recursively using

$$\min_{K,L} \quad r(1+\eta_K)+wL \tag{36}$$

$$s.t. \quad G=TFPQ1\cdot f(K,L), \tag{37}$$

and recovering the $TFPQ_1$ which would yield the unit cost function (that we derived using our 4-staged decision program) specified at (26) as

$$c = \frac{(1+\phi)^{\alpha}}{z} \left(\left(\frac{\alpha}{\lambda}\right)^{\frac{1}{\rho}} \frac{r(1+\eta_K)}{\alpha} \right)^{\alpha} \left(\left(\frac{1-\alpha}{1-\lambda}\right)^{\frac{1}{\rho}} \frac{w}{1-\alpha} \right)^{1-\alpha} \left(1+\alpha\left((1+\phi)^{\frac{\rho}{1-\rho}}-1\right)\right)^{\frac{\rho-1}{\rho}}.$$

The production function in the form of $TFPQ1 \cdot f(K,L)$ that yields (26) is uniquely expressed as

$$G = z\left[\frac{\lambda^{\alpha}(1-\lambda)^{1-\alpha}}{\alpha^{\alpha}(1-\alpha)^{1-\alpha}}\right]^{\frac{1}{\rho}} (1+\phi)^{-\alpha} \left(1+\alpha((1+\phi)^{\frac{\rho}{1-\rho}}-1)\right)^{\frac{1-\rho}{\rho}} \cdot \underbrace{K^{\alpha}L^{1-\alpha}}_{=f(K,L)},$$

with

$$TFPQ1 = \hat{z}\left[\alpha^{\alpha}(1-\alpha)^{1-\alpha}\right]^{\frac{-1}{\rho}} (1+\phi)^{-\alpha} \left(1+\alpha((1+\phi)^{\frac{\rho}{1-\rho}}-1)\right)^{\frac{1-\rho}{\rho}}, \tag{38}$$

where $TFPQ1$ is maximized at $\phi^* = 0$.

Having specified $TFPQ1$, next we measure TFPR1, where $TFPR1 = p \cdot TFPQ1$ as standard in the literature. Using the pricing equation (16) and the expression for $TFPQ1$ at (38) we get

$$TFPR1 = \frac{\sigma}{\sigma-1}\left(\frac{r}{\alpha}\right)^{\alpha}\left(\frac{w}{1-\alpha}\right)^{1-\alpha}\frac{(1+\eta_K)^{\alpha}}{1-\eta_Y}, \tag{39}$$

which is identical to the TFPR measure of Hsieh and Klenow (2009).

As our second TFPQ measure, which we call $TFPQ2$, we set

$$TFPQ2 = \hat{z} = z\left[\lambda^{\alpha}(1-\lambda)^{1-\alpha}\right]^{\frac{1}{\rho}}, \tag{40}$$

and then from $TFPR2 = p \cdot TFPQ2$, we obtain

$$TFPR2 = \frac{\sigma}{\sigma-1}\left(\frac{r}{\alpha}\right)^{\alpha}\left(\frac{w}{1-\alpha}\right)^{1-\alpha}\frac{(1+\eta_K)^{\alpha}}{1-\eta_Y}(1+\phi)^{\alpha}\left(1+\alpha((1+\phi)^{\frac{\rho}{1-\rho}}-1)\right)^{\frac{\rho-1}{\rho}}. \tag{41}$$

We can notice three important features of the two alternative physical productivity specifications, namely $TFPQ1$ and $TFPQ2$:

1. Factor and output distortions ($\eta_K,\ \eta_Y$) only affect $TFPR$ in both specifications.

2. Technique distortions (ϕ) only affect $TFPQ1$ in the first specification.

3. Technique distortions (ϕ) only affect $TFPR2$ in the second specification.

4. Therefore, while TFPQ1 measure accounts all gains from improving technique distortions to the physical productivity, the TFPQ2 measure accounts all technique distortion gains to the revenue productivity.

As we will delineate in the next section these two alternative TFPQ (and TFPR) specifications provide quantitatively similar insights when measuring the aggregate industry TFP and estimating the TFP effects of firm-specific distortions. This property is essential because it will ensure that our quantitative findings are not sensitive to special-case measurements of firm-level productivities (i.e., $(TFPQ1, TFPR1)$ vs. $(TFPQ2, TFPR2)$).

6.3 Industry-level Total Factor Productivity

We are now ready to develop a measure for industry-level TFP. In order to do so, we first observe that the aggregate price index for an industry – composed of M firms – is given by

$$P = \left(\sum_{i=1}^{M} p^{\sigma-1} \right)^{\frac{1}{\sigma-1}}.$$

Using $TFPR = p \cdot TFPQ$, we can re-write the aggregate price index as

$$P = \left(\sum_{i=1}^{M} \left(\frac{TFPQ}{TFPR} \right)^{\sigma-1} \right)^{\frac{1}{\sigma-1}}. \tag{42}$$

Denoting the industry-level aggregate revenue productivity with $\overline{TFPR}$, we can observe that

$$P = \frac{\overline{TFPR}}{TFP},$$

using which together with (42) we express a closed-form measure of industry-wide TFP.

$$TFP = \left(\sum_{i=1}^{M} \left(TFPQ \frac{\overline{TFPR}}{TFPR} \right)^{\sigma-1} \right)^{\frac{1}{\sigma-1}}. \tag{43}$$

Finally, we note that the industry-wide aggregate $\overline{TFPR}$ can be recovered as

$$\overline{TFPR} = \frac{\sigma}{\sigma-1} \left(\frac{r}{\alpha} \right)^{\alpha} \left(\frac{w}{1-\alpha} \right)^{1-\alpha} \frac{(\overline{1+\eta_K})^{\alpha}}{\overline{1-\eta_Y}} (\overline{1+\phi})^{\alpha} \left(1 + \alpha((\overline{1+\phi})^{\frac{\rho}{1-\rho}} - 1) \right)^{\frac{\rho-1}{\rho}}, \tag{44}$$

where $\overline{1+\eta_K}$, $\overline{1-\eta_Y}$, and $\overline{1+\phi}$ are industry-wide averages across firms. Finally, we note from (43) that – as in standard models of misallocation and TFP – when firm-level TFPR across all firms are equalized in an industry, such that $TFPR = \overline{TFPR}$ for every firm, industry-wide TFP becomes a function of the aggregation of firm-level TFPQs.

7 Quantitative Analysis

We have established several important properties of a generalized production framework with endogenous techniques choice and distortions. We are now prepared to utilize firm-level data and conduct quantitative exercises to illustrate the effects of capital, output and technique distortions on aggregate industry-TFPs.

7.1 Firm-level Data

To conduct our quantitative analysis, we use firm-level balance sheet data, for publicly traded-firms, from Compustat North America's Fundamentals Annual database. For this purpose we use several waves of cross-sectional manufacturing sector data between the years of 1995 and 2015. For our aggregation analysis, we concentrate on the 4-digit SIC manufacturing industry clusters that we list in Table 1, which are "Food & Tobacco", "Paper & Printing", "Chemicals and Petrol-Rubber-Plastic", "Primary & Fabricated Metal", "Machinery Manufacturing", "Electrical Equipment Manufacturing", and "Transportation Equipment Manufacturing".

The key firm-level variables that are required for our identification and aggregation purposes are annual figures for *labor*, *capital*, *total cost of labor*, *total cost of capital* and *total revenues from sales*. We construct the variables of interest as follows.

1. **Labor** (L) is captured by the *total number of employees* data item in Compustat North America Fundamentals Annual (the name of the variable in the database is *emp*).

2. **Capital** (K) is generated by applying the inventory accumulation method using *property, plant and equipment gross and net totals* data items in Compustat North America Fundamentals Annual (data-names *ppegt* and *ppent*).[9]

3. **Total labor cost** (wL) is captured by the *total staff expense* data item in Compustat North America Fundamentals Annual (data name *xlr*).

4. **Total capital cost** $(r(1+\eta_K)K)$ is generated by summing up the *capital expenditures* data item in Compustat North America Fundamentals Annual for the current period with $r(1-\delta)K$ from the previous period, where $r = 1.1$ and $\delta = 0.05$ as in Hsieh Klenow (2009). (data name for capital expenditures is *capx*).

5. **Total revenue** (TR) is captured by the total revenue data item in Compustat North America Fundamentals Annual (data name *revt*).

In Table 5 we provide descriptive statistics with respect to the distribution of these five firm-level variables across establishments for the years between 1995-2014 in manufacturing industry clusters that we focus on in the quantitative analysis.

The industry-level parameters are extracted from NBER productivity database and existing research. To summarize again, (i) capital's share in technology menu (α) is computed using the NBER productivity database and (ii) industry-level production flexibility parameter estimates (ρ) are from Oberfield and Raval (2014) and Raval (2015). To the end of the latter, the authors utilize U.S. manufacturing data between 1987-2007 in order to estimate factor substitutability parameters for a generalized CES production function. Both α and ρ vary across manufacturing industry-clusters

[9]We apply the inventory accumulation as follows. We set the value of the initial capital stock equal to the first available entry of ppegt. After having set the value of the initial capital stock we let the capital accumulate using $k_{it} = (1-\delta)k_{it-1} + i_{it}$, where we compute the net investment as $i_{it} - \delta k_{it} = ppent_{it+1} - ppent_{it}$.

as we document in Table 2. To the end of the key industry-level production flexibility parameter of the framework, we note that "Food & Tobacco" and "Transportation Equipment Manufacturing" industries are the most flexible industry-clusters whereas "Primary & Fabricated Metal" industry is the least flexible industry.

Finally we set $\sigma = 3$ as a benchmark value so that our quantitative strategy and findings can be comparable to the existing literature. In Section 7.4.2 we will check the sensitivity of our results with respect to variations in r and σ.

7.2 Benchmark

Based on the data items listed above we execute the identification strategy, proxy firm level measures of TFPQ and TFPR (using the two alternative methods, $(TFPQi, TFPRi)$, $i = 1, 2$) and finally quantify the benchmark TFP by using the aggregation rule (43) for each industry-cluster over the time-period 1995-2015 - as we described in Section 6. As an important quantitative feature of the benchmark framework, we choose the limit techniques $\underline{a}_K$ and $\underline{a}_L$ such that the distribution of technique distortions satisfies $\phi \in [0.999, 30]$ in every industry-cluster. In this section, as well as in the rest of the quantitative analysis, we present results for the years of 1995, 2005 and 2014, where 2014 is the last year of observations in our data. In the Online Appendix we provide results for additional years between 1996-2012.

Table 6 presents relative TFP estimates across the distribution of manufacturing industry-clusters. When presenting the TFP estimates, in each year we set the TFP of the industry-cluster with the lowest measured TFP in a particular year equal to 1 and then provide the TFP estimate of each industry relative to this base-industry.

The TFP estimates in Table 6 reveal that the ranking of the TFPs across the 7 manufacturing industry clusters largely remains the same when TFPs are ranked according to the physical productivity measure TFPQ1 or according to the measure TFPQ2. Specifically, in years 2005 and 2014 the TFP-ranking of industries coincide completely with TFPQ1 and TFPQ2 physical-productivity measures. For the year of 1995 the ranking of TFPs is mostly unaltered as well when switching from TFPQ1 measure to TFPQ2, with the exception that the most- and the second-most productive industries change ordering when the physical productivity measurement is altered.

In Tables 7a-7c, we provide distributional properties with respect to TFPQ and TFPR measures – in logs, whose aggregations provide the TFP estimates presented in Table 6. For each industry-cluster, the distributional properties of TFPQ1, TFPR1 and TFPR2 are relatively stable over-time. In Table 7 we do not provide the properties of TFPQ2 measure, to which we refer in the next block of tables, because $TFPQ2 = \hat{z}$.

In Tables 8a-8d we present the distributional properties (means and standard deviations) of firm-specific distortions η_K, η_Y and ϕ and also firm-level technology frontier $\hat{z}$. Table 8a illustrates that from 1995 to 2014 the average firm across all manufacturing industries switched from being slightly subsidized to being slightly taxed when it comes to capital distortions. For output distortions, η_Y's, as presented in Table 8b, a wide dispersion is observed for many industries, which will turn out to be important for misallocation and TFP accounting. Importantly, technique distortions, ϕ's, are different than zero-optimum throughout the years and across the industry clusters – with significantly large dispersions, which promotes technique distortions as a potentially important barrier for TFP growth. Finally, Table 8d shows that the distribution of $\ln(\hat{z})$ (equivalent to TFPQ2) is relatively stable over-time, aligning with the stability of over-time variation in TFPQ1, TFPR1 and TFPR2 that we established in Tables 7a-7c.

7.3 Counterfactual Experiments with the Benchmark TFP Specification

We use the TFP measure developed at (43) in order to conduct counterfactual quantitative experiments and to understand by what proportion the TFP of each manufacturing industry-cluster would rise (or deteriorate) if we were to reduce the distortions originating from capital, output and technique decisions of the production process.

Before we proceed with our results we would like to note that for the case of TFPQ2 measure, we will only provide quantitative results with respect to technique distortions, because the measured impacts of capital and output distortions on industry-TFPs do not vary with the measurement of TFPQ. This is the case because capital and output distortions affect the industry TFP through firm-specific TFPR dispersion under both TFPQ specifications. Finally, the counterfactuals presented in this section focus on the years of 1995, 2005 and 2014 while a wider coverage of counterfactual TFP results over the period 1996-2012 are reported in the Online Appendix Tables OA1a-OA1d.

7.3.1 Reducing Distortions under Productivity Measures (TFPQ1,TFPR1)

We set each distortion one-at-a-time for each firm equal to zero and compute the resulting TFP gains (or losses). Specifically, in each quantitative exercise we shut down a particular source of heterogeneity resulting from capital, output or technique distortions, respectively by setting $\eta_K = 0$, or $\eta_Y = 0$, or $\phi = 0$ for all firms in an industry, re-compute firm-level TFPQs and TFPRs resulting from this exercise, measure the counterfactual TFP and report the ratio between the counterfactual TFP and the benchmark TFP in Tables 9a-9d. Therefore, in Tables 9a-9d as well as in all counterfactual experiment tables of the quantitative analysis $\Delta TFP > 1$ indicates an expansion in the industry-TFP after the removal of the distortions, whereas $\Delta TFP < 1$ implies a contraction.

In Table 9a we report the TFP gains resulting from setting $\eta_K = 0$ for all firms. When $\eta_K = 0$ is set for all firms, this also affects the industry-wide $\overline{TFPR}$, which contains a geometric average of capital distortions. Taking into account this implication of the quantitative experiment for the aggregate industry revenue productivity along-side the implied changes in firm-specific revenue productivities, we re-compute the resulting TFP using (43) and report the ratio between the counterfactual TFP and the benchmark TFP in Table 9a.

The results in Table 9a reveal that *the dispersions in capital distortions are not very important in determining industry-TFPs for manufacturing industry-clusters.* Specifically, reducing capital distortions (both taxes and subsidies) to zero for all firms raises the industry TFP only marginally. For the year of 2014, the largest impact of eliminating capital distortions are obtained for the cases of "Electrical Equipment" and "Metal" industry-clusters, respectively, with 3.4% and 1.6% expansion of the aggregate industry-TFP. In 2014, for the remaining industry-clusters, the effects of capital distortions and the resulting misallocation on industry TFPs are less than 1%. The overall effect of "capital misallocation" on industry TFPs is smaller for the years of 1995 and 2005 – with negative net aggregate effects of removing capital distortions fully for the case of some industries (such as "Paper" and "Metal" in 1995 and "Food", "Metal" and "Machinery" in 2005). The reason for such negative consequences from removing capital distortions is associated with "subsidized capital finance" on average, which can be observed from the distributional properties of η_K that we present in Table 8a.

The negligible TFP consequences of capital distortions that we capture in our framework aligns with the findings of Gilchrist, Sim and Zakrajsek (2013). Using a measured TFP approach and secondary bond price data for publicly traded firms from the U.S., Gilchrist, Sim and Zakrajsek (2013) show that the dispersion in borrowing costs observed in the bond-price data for manufacturing firms results in an efficiency loss due to capital misallocation which is equivalent of 1-to-2 percent of the measured benchmark TFP. Our overall findings with respect to the TFP effects of capital distortions are also within the range of few percentage points as we present in Table 9a.

We then proceed and report in Table 9b the TFP effects from setting the output distortions equal to $\eta_Y = 0$ for all firms. Similar to the case of η_K, when $\eta_Y = 0$ is set for all firms, this affects the industry-wide $\overline{TFPR}$. The quantitative results show that *the role of output distortions is much more substantial compared to capital distortions in determining TFP losses.* Even when a few outlier-cases are put aside, the overall positive TFP effects of output distortions are as high as 80-90% ("Machinery" and "Electrical Equipment" industry-clusters) of the benchmark TFP – with 30-40% potential TFP gains on average across clusters of manufacturing industries and over time from removing output distortions.

Finally, Table 9c reports the TFP effects resulting from setting $\phi = 0$ for all firms. Different from the cases of $\eta_K = 0$ and $\eta_Y = 0$, when ϕ distortions are shut down to zero for all firms under the TFPQ1 measure, industry-wide TFPR is not affected – with productivity gains channeled through the increases in firm-specific TFPQs only. The results show that *technique distortions are quantitatively very significant in generating efficiency losses and reducing industry TFPs, where in* *some industry cases (such as 5 out of 7 industries for the year of 2014) the TFP effects of technique distortions are even stronger than those of output distortions.* In all three years, for which we provide quantitative results, reducing the technique distortions to zero for all firms results in TFP gains that for most industries exceed 100% of the benchmark industry TFP.

As we illustrate in the Online Appendix Tables OA1a-OA1d, strong and persistent quantitative effects of technique distortions and relatively negligible effects of capital distortions are present not only for a selected few years, but for a wide coverage of years between 1996-2012.

7.3.2 Reducing Distortions under Productivity Measures (TFPQ2,TFPR2)

We repeat the previous quantitative analysis for the case of TFPQ2 measure in order to ensure the robustness of our quantitative results with respect to the measurement of physical productivity of firms. As already highlighted before, when doing that, we only provide results from technique distortion exercises, since the implications of capital and output distortions for industry TFPs remain the same under the two alternative TFPQ measures.

In this alternative framework the TFP effects of technique distortions get channeled through the TFPR dispersion. We again set ϕ equal to zero for all firms and compute TFP effects in every industry-cluster and report them in Table 9d. Our results indicate that, *although the TFP effects of technique distortions slightly contract under the TFPQ2 measure, the overall effects remain substantially large* throughout the years and across the manufacturing industry clusters. One exception to this pattern is the "Food-Tobacco" industry for the year of 2005: in that particular year, the variance of technique distortions equals to zero for the Food-Tobacco industry and hence there are no TFPR-dispersion driven gains to be obtained for the aggregate industry TFP.

We conclude that the two alternative productivity measures that we construct generate overall comparable TFP effects of technique distortions. Thus, our main quantitative findings are not sensitive to special-case measurements of firm-level productivities.

7.3.3 Industry Flexibility ρ and TFP Gains

The results presented in Tables 9c and 9d reveal the substantial implications of technique distortions for industry TFPs. An important feature of our theoretical structure is the mitigating effect of industrial production flexibility, ρ, on counterproductive consequences of technique distortions. Next we investigate the quantitative relevance of this theoretical channel. Specifically, we are interested in addressing the following question: How does the industry-level production flexibility affect the TFP consequences of technique distortions?

As one can observe in the expressions for TFPQ1 (at (38)) and TFPR2 (at (41)), flexibility of production mitigates technique distortions in generating efficiency losses for industry TFPs as long as the conditions set at item (iii) of Proposition 4.1 hold. We first note that the condition (iii-a) holds for all industries except for "Food & Tobacco" industry. Second, the lower limit $\underline{a}_L$ that we impose at the industry level ensures that the condition (iii-b) holds for the "Food & Tobacco" industry. Therefore, for all industries in our quantitative framework the conditions of Proposition 4.1 get satisfied; and hence, theoretically the higher the industry-level flexibility of production the lower should be the distortionary effects of technique distortions. Hence, the TFP gains from removing technique distortions are expected to be the highest in industries in which the efficient units of capital and labor are strong complements.

The quantitative results in Tables 9c and 9d are in line with this key theoretical prediction. The industries with the lowest level of production flexibility (where factors are more complementary), as we presented in Table 2, are "Metal", "Paper" and "Chemicals". When focusing on the average TFP gains over the three years of our study, these industries feature the largest measured TFP gains from removing technique distortions. On the other extreme, "Food-Tobacco" industry has the highest production flexibility (where factors are more substitutive), which also turns out to have the smallest measured TFP gains from correcting technique distortions. Machinery, Electrical Equipments and Transportation Equipments industries have intermediate levels of flexibility and these industries have mediocre potential of TFP-growth from correcting technique distortions.

In order to deepen our understanding on the interaction of industry-flexibility with technique distortions and the quantitative implications of this interaction, we conduct another set of counterfactuals: In Tables 9e-9h we raise the level of production of flexibility for each industry to -0.15, which is the level of production flexibility of the Food-Tobacco industry. This allows us to account for the contribution of ρ in explaining the variation in TFP gains across industry-clusters from correcting distortions. Before we present the quantitative results we note that "counterfactual TFP exercises with the counterfactual-ρ" generate two opposing effects resulting from the expansion in ρ. On the one hand, as we discussed above in detail, the rise in ρ lowers the benefits from reducing technique distortions. This property follows from Proposition 4.1. On the other hand, increasing ρ raises TFP because of its direct impact on TFPQ1 as well as TFPQ2, a property which follows from the result in Proposition 3.2. If the former effect is strong enough to dominate the latter, compared to what we have obtained in Tables 9c and 9d, we should record quantitatively smaller TFP expansions from ϕ-counterfactuals in Tables 9g and 9h.

The results in Tables 9e-9h reveal that for almost all industry-year combinations the mitigation effect of ρ is quite strong such that production flexibility explains a large fraction of the TFP gains from reducing technique distortions. Although the TFP gains from reducing η_K and η_Y distortions do also change slightly when, ceteris paribus, ρ is increased to the level of Food-Tobacco industry, the reductions in TFP gains from removing technique distortions contract substantially: by raising ρ of each industry to the level of the industry with the lowest ρ we observe that a large part of the inter-industry variation in TFP-gains from reducing technique distortions vanishes. As we also report in

Tables 9g and 9h, 40-80% of TFP gains from reducing technique distortions are explained by the difference between the actual flexibility of production in a particular industry and the flexibility of production of the Food-Tobacco industry. Hence, we conclude that industry-wide production flexibility is a quantitatively important component to explain the TFP consequences of technique distortions.

7.4 Robustness

In this section we test the sensitivity of our main findings with respect to the specification of production framework, the benchmark values of macro parameters, outliers and finally the mismeasurement of firm-level variables.

7.4.1 Comparison with the Special Case of Neoclassical Production Function

We study counterfactual experiments in an hypothetical environment, where firm-level $TFPQ$ is given by $TFPQ = \hat{z}$, $a_K = a_L = \hat{z}$ is exogenously set for all firms and there is no flexible techniques decision-making at the firm-level. This specification represents the framework of a Neoclassical Production Framework: firms choose optimal factor quantities to minimize the unit cost of production, given a production technology specified as

$$Y = z\left[\lambda K^{\rho} + (1-\lambda)L^{\rho}\right]^{\frac{1}{\rho}}. \tag{45}$$

Using this framework we conduct a set of quantitative experiments, where we reduce capital and output distortions to zero when the technology is given by (45) and the firms are subject to heterogenous factor (η_K) and output (η_Y) distortions, which we continue to back out using (31) and (34). The results from shutting η_K and η_Y distortions to zero are presented in Tables 10a and 10b for the years of 1995, 2005 and 2014. The results indicate that capital distortions are essentially negligible while output distortions are substantial in determining the TFP efficiency losses – aligning with a key finding from the benchmark analysis. This quantitative property provides a robustness check for that the results that we obtained with respective to the relative importance of capital and output distortions for TFP in our benchmark specification are not artifact of the way we specified the benchmark production framework.

7.4.2 Sensitivity to r and σ

Following a standard practice in the misalloaction literature, we had exogenously specified the values of two parameters of the model: The average cost of capital r and the elasticity of substitution across varieties, captured by σ. When choosing the values for these parameters we followed the benchmark parameterization assumptions of Hsieh and Klenow (2009) and set $r = 1.1$ and $\sigma = 3$. In Tables

11a-b and 12a-b we check the sensitivity of our TFP counterfactual results with respect to variations in r and σ, where in Tables 11a and 11b we vary the value of σ to 2 and 4 and in Tables 12a and 12b we vary the value of r to 1.07 and 1.13 from benchmark values. We report counterfactual TFP results from shutting down η_K, η_Y, ϕ (with TFPQ1 and TFPQ2 measures) one at-a-time as we did in benchmark exercises.

To preserve space we provide the sensitivity analysis only for the year of 2014, although quantitative results that we do not report here are quite comparable for the years of 1995 and 2005. The counterfactual TFP results from these alternative specifications exhibit no change from our previous primary quantitative findings: (i) Capital distortions are relatively negligible next to output and technique distortions in determining industry TFPs, (ii) both output and technique distortions are quantitatively substantial for efficiency losses, (iii) with the exception of "Food-Tobacco" and "Chemicals" industry-clusters technique distortions account for the largest efficiency losses in manufacturing industries, (iv) ρ mitigates the distortionary effects of technique distortions and (v) the magnitude of the quantitative effects that we capture in each counterfactual experiment throughout the alternative specifications are comparable to the benchmark quantitative effects that we report in Tables 9a-9d.

7.4.3 Outliers

Next we perform a robustness test by eliminating outlier-firms from the analysis based on the level of revenue productivities (with measures of TFPR1 and TFPR2) for the year of 2014. Before we present the analysis, we first note that when backing out the technique distortions we already truncated the distribution of TFPQs and TFPRs across firms by limiting the extreme values that ϕ can take. In the counterfactual TFP analysis of Table 13a (and in 13b) we take a further step and leave out any firm from our analysis whose TFPR1 (and TFPR2) takes a value that is not within 1.5 standard deviation of industry's mean TFPR1 (and TFPR2) for the year of 2014. The resulting sample sizes (relative to the benchmark sample size) from this exercise are presented in the last columns of Tables 13a and 13b.

As the last columns of Tables 13a and 13b document, the sample sizes shrink by 10-20% when we perform this sub-sample analysis. However, the primary quantitative findings from the benchmark analysis fully remain. Capital distortions are negligible and with the exception of Food-Tobacco and Chemicals industry-clusters technique distortions account for the largest efficiency losses in manufacturing industries – followed by output distortions. The industry-level production flexibility, ρ, is a quantitatively important mitigator of technique distortions. Finally, the magnitude of the TFP effects of each distortion that we capture after getting rid off outlier observations are highly comparable to the benchmark quantitative effects in Tables 9a-9d.

7.4.4 Mismeasurement

There are five firm-level variables that we utilize in the quantitative analysis: Revenues, number of employees, total cost of labor, capital stock, and total cost of capital. Among these five variables, capital stock and total cost of capital are the two variables which might be prone to some mismeasurement issues. In this section we provide robustness checks to address concerns regarding the mismeasurement of capital stock and the total cost of capital, where we delineate a theoretical discussion with respect to the former and a quantitative analysis to address the latter.

At first we consider the case of mismeasured capital stock. Specifically, we suppose that the "capital stock" measure that we observe, call it $\hat{K}$ from now on, is a distorted version of the actual capital stock utilized by the firm (denoted with K). We note that the measurement problem is not with "total capital expenditures" but with "capital stock". That is $\hat{K}(1+u_K) = K$, where u_K is a firm-specific capital mismeasurement distortion. Then the maximization program stays the same for the firm as we have analyzed previously (with 3 distortions), but the K/L ratio equation, whose left-hand-side comes from the data becomes:

$$\frac{\hat{K}}{L} = \frac{w}{r}\frac{\alpha}{1-\alpha} \cdot \frac{(1+\phi)^{\frac{\rho}{1-\rho}}}{1+\eta_K}\frac{1}{1+u_K}.$$

Then, the 3 equations to be utilized to back out distortions become:

$$1-\eta_Y = \frac{\sigma}{\sigma-1}\frac{TC}{pY}. \tag{46}$$

$$1+\phi = \left\{\frac{1-\alpha}{\alpha}\left[\frac{TC}{wL}-1\right]\right\}^{\frac{1-\rho}{\rho}}. \tag{47}$$

$$(1+\eta_K)(1+u_K) = \frac{wL}{r\hat{K}}\left[\frac{TC}{wL}-1\right]. \tag{48}$$

The output distortion η_Y still gets uniquely identified by (46) and ϕ is uniquely identified by (47), whereas $(1+\eta_K)(1+u_K)$ gets jointly identified through (48) but we cannot decouple η_K and u_K. Hence, even if we allow for a fourth firm-level distortion as mismeasured capital, we can still identify ϕ – exactly the way we identified it in the benchmark framework – as well as the output distortion η_Y. This property is a theoretical robustness check for the identification of technique distortion term ϕ.

Since allowing for mismeasured capital stock does not affect the identification of technique and output distortions, it does not influence their quantitative impact on TFP either. Identification of capital distortions could of course get affected by capital-stock mismeasurement. But, given the relatively negligible quantitative effects of capital distortions that we captured – that are also comparable to the previous findings of the literature – we move on and study the quantitative implications of mismeasured total cost of capital.

Mismeasured cost of capital could affect the identification of distortions. Since we cannot observe mismeasurement in cost of capital at the firm-level, we study two aggregate cases that we present in

Tables 14a and 14b. In the TFP counterfactuals that we investigate in these two tables, we assume that the total cost of capital is larger (smaller) than the benchmark measurement by 15% in the analysis of Table 14a (Table 14b) and investigate the TFP efficiency loss implications of capital, output and technique distortions, by shutting down η_K, η_Y and ϕ to zero one-at-a-time for the year of 2014. The results that we present in Tables 14a and 14b reveal that the counterfactual TFP results we obtained in the benchmark framework are robust to a uniform mismeasurement of total cost of capital across firms: Specifically, assuming that the total cost of capital is systematically larger (or smaller) than what we captured in the benchmark framework for all firms does not alter the key findings that capital distortions are relatively negligible, whereas primarily technique and then output distortions are key drivers of TFP efficiency losses.

7.5 Cross-Country Comparisons

A final question that we would like to tackle is whether persistent and quantitatively significant efficiency losses associated with technique distortions are visible in developing-country firm-level data as well. If so, this would have important development policy implications. In order to address this point we refer to the Global-database of Compustat for publicly-traded firm-level data from China and India. We choose the Compustat Global-data for the cross-country analysis in order to work with data-sets that are by nature comparable to the U.S. Benchmark: working with Compustat Global allows to compare publicly traded firms in the U.S. with the publicly traded firms in the context of developing countries.

Publicly traded firms in developing countries are expected to be large firms as well (as for the case of the U.S.) to not face heavy distortionary taxes when financing capital inputs. Such publicly traded firms are expected not to be subject of heavy financial market imperfections, which loom large in developing countries. If at all, they might be even on the beneficiary-side of financial frictions. However, technique distortions could also be important for the efficiency losses of publicly traded firms in developing countries.

Tables 15a and 15b present descriptive statistics of firm-level variables for the country-cases of India and China using data from Compustat Global Fundamentals Annual for the years between 1995-2014. When compared against what we have presented in Table 5 (for the U.S. Benchmark), the distributional properties in Tables 15a-15b exhibit firm-size distributions that are skewed towards larger scale establishments in both China and India.

We then back-out distortions and technology frontiers at firm-level – using the benchmark U.S. parameters, and then conduct the TFP counterfactual analyses: we shut down each source of distortion one-at-a-time and present the ratio between the resulting counterfactual TFP and the benchmark TFP in Tables 16a-16b (17a-17b) for India (for China). Because of the limited availability of manufacturing data observations in the year of 1995 for India and China we report results only for the years of 2005 and 2014. Furthermore, for the case of China in 2005 manufacturing data for Food-Tobacco and Paper industry clusters are not available.

Tables 16a and 17a exhibit that for Indian and Chinese manufacturing industries reducing the capital distortions as a whole do not stimulate the aggregate TFPs any more than they would for U.S. manufacturing industries. And, in some industry clusters reducing capital distortions lower industry TFPs. This quantitative result we explain by the "relatively large" firms that we get to study when using Compustat Global data.

Moving onto output distortions, for both China and India we observe that in both 2005 and 2014 shutting down $\eta_Y = 0$ increases TFP by quantitatively significant proportions, for most of the manufacturing industries. This is a similar pattern that we had also obtained for the U.S. benchmark.

Importantly, *removing technique distortions results in substantial TFP gains in both China and India*: In both years of the analysis, technique distortions generate substantial efficiency losses for the aggregate industry-TFPs – with larger TFP gains from correcting technique distortions in industries with low production flexibility. Also, when compared against the efficiency effects of technique distortions in the U.S., in China and India the effects of technique distortions are not any lower than those of in the U.S. benchmark. This quantitative result suggests that technique distortions should be regarded as an important issue for developing countries as well.

8 Concluding Remarks

We have developed a generalized production framework, embedding a deep flexibility concept, where firms decide on their factor inputs as well as production techniques that determine the efficient use of factors under currently operating technologies. We have characterized factor demands, techniques choice and the unit cost of production. By allowing firms to differ in technology frontiers, capital finance frictions, techniques and output distortions, we have developed an aggregated measure of industry TFP. We have then examined the consequences of capital, output and technique distortions for the aggregate productivity as well as the interplay of the TFP effects of distortions with industry-level production flexibility, by also providing an empirical justification for our theoretical structure.

The theoretical results indicate that while both capital finance and technique distortions raise the unit cost of production, substitutability between technique augmented factors reduces the efficiency losses borne by technique distortions: The detrimental effects of capital financing distortions are independent of the extent of industry-level production flexibility, but the detrimental effects of technique capability distortions are amplified by industry's production flexibility.

We have undertaken a number of quantitative exercises by calibrating the model to fit the observations from firm-level data in U.S. manufacturing industries. Our quantitative results can be summarized as the following:

1. For all manufacturing industry-clusters – throughout the years of the analysis – technique distortions and output distortions account for substantial efficiency losses at the level of industry TFPs.

2. The impact of technique distortions in generating efficiency losses in the aggregate is larger than that of the output distortions for many industry-clusters and over time.

3. The inefficiency impact of technique distortions get mitigated by the industry-wide flexibility of production. This means, TFP gains from removing technique distortions are larger in industries where efficient units of capital and labor exhibit strong complementarity.

4. Capital distortions have a relatively negligible impact on industry-level TFPs – matching the findings of past research which have utilized similar datasets.

5. Our key quantitative finding – that technique distortions are significantly more important than capital finance distortions and at least as important as output distortions for industry TFPs – is robust to the measurement of firm-level productivity, parameter specifications, outliers and the mismeasurement of capital-stock and total cost of capital variables.

6. We also conduct quantitative experiments for two developing countries, namely for India and China. Cross-country comparisons with Chinese and Indian firm-level data show that technique distortions are the most substantial source of TFP-efficiency losses in these two developing countries as well.

An important policy implication arising from our analysis is that to achieve greater production efficiency, mitigating technique distortions should be granted with high priority. Such policy arrangement may include, but not limited to, tax incentives for adjusting production techniques and subsidies for flexible manufacturing systems, both on equal grounds for all firms in the same industry.

There are several extensions that can build upon the analysis of this paper, such as the investigation of the interplay between technique flexibility and industry flexibility on extensive margin misallocation, the analysis of different market structures in driving the importance of technique distortions for the aggregate productivity and endogenizing technique distortions. These extensions we leave to future work.

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Table 1. Classification of Manufacturing Industries

Industry Cluster	4-digit SIC Classification
Food-Tobacco	2000-2199
Paper-Printing	2600-2799
Chemichal-Petrol-Rubber/Plastic	2800-3099
Primary/Fabricated Metal	3300-3499
Machinery (Industrial+Commercial+Computer)	3500-3599
Electrical Equipment	3600-3699
Transportation Equipment	3700-3799

Table 2. Structural Parameters

Industry Cluster	α	ρ
Food-Tobacco	0.22	-0.15
Paper-Printing	0.25	-1.5
Chemichal-Petrol-Rubber/Plastic	0.39	-1.08
Primary/Fabricated Metal	0.42	-2.92
Machinery	0.12	-0.92
Electrical Equipment	0.14	-0.96
Transportation Equipment	0.23	-0.3

Table Notes. Share of capital in technology menu, α, is from NBER Productivity Database. Industry-level production flexibility, ρ, is from Oberfield and Raval (2014) and Raval (2015), who estimate flexibility of production parameters for a variety of manufacturing industries using Census data from the time period 1987-2007.

Table 3a. Distributional Properties of τ_K

Industry Cluster	Mean	Std. Dev.	Min	Max	# Obs.
Food-Tobacco	-0.89	0.37	-0.99	4.04	434
Paper-Printing	-0.87	0.35	-0.99	8.07	815
Chemichal-Petrol-Rubber/Plastic	-0.70	2.16	-1	49.59	2,077
Primary/Fabricated Metal	-0.80	0.55	-0.99	3.29	452
Machinery	-0.71	0.49	-0.99	5.33	425
Electrical Equipment	-0.12	3.63	-0.99	45.63	672
Transportation Equipment	-0.83	0.30	-0.99	2.14	593

Table Notes. τ_K is identified using the structural equation (28).

Table 3b. Distributional Properties of τ_Y

Industry Cluster	Mean	Std. Dev.	Min	Max	# Obs.
Food-Tobacco	0.20	5.16	-85.37	0.99	434
Paper-Printing	0.22	6.56	-181.49	0.99	815
Chemichal-Petrol-Rubber/Plastic	-7.34	156.68	-6683.07	0.99	2,077
Primary/Fabricated Metal	0.49	0.32	-1.59	0.97	452
Machinery	-1.67	28.12	-557.86	0.99	425
Electrical Equipment	-2.85	34.28	-784.81	0.99	672
Transportation Equipment	0.29	4.39	-103.67	0.97	593

Table Notes. τ_Y is identified using the structural equation (29).

Table 4. τ_Y and τ_K: Regression with τ_Y on the LHS

τ_K	-3.71***
	(1.44)
R&D per Employee	-0.071
	(0.12)
Assets per Employee	-0.0028
	(0.0026)
Intangible Assets per Emp	0.015
	(0.013)
Earnings Ret. per Emp	-0.00054
	(0.0010)
Long-Term Debt per Emp	-0.011
	(0.014)
Profits per Emp	0.055***
	(0.014)
Industry FE	Yes
Year FE	Yes
Observations	2,334
R-sq	0.0246

Table Notes. Firm-level variables are from Compustat North America Fundamentals Annual for the years between 1995-2014. Structural distortions τ_K and τ_Y are identified using equations (28) and (29) respectively. The regressions use firm-level information for the years between 1995-2014 from manufacturing industry clusters listed in Table 1. We trim outliers by imposing $\tau_Y < 1$ and $\tau_K < 50$.

Table 5. Distributional Properties of Firm-Variables

Variable Name	Mean	Std. Dev.	Min	Max	# Obs.
ln(Labor)	6.47	2.41	0	13.52	50805
ln(Capital)	17.29	3.01	6.90	26.54	56077
ln(Total Labor Cost)	18.02	3.40	9.10	25.59	5116
ln(Total Capital Cost)	17.32	3.09	6.90	26.65	55955
ln(Total Revenue)	18.62	2.96	6.90	26.88	54476

Table Notes. Firm-level averages are from Compustat North America Fundamentals Annual for the years between 1995-2014 – from firms operational in manufacturing industry-clusters presented in Table 1. Labor is in units of employees whereas the other firm-level variables are in dollar values.

Table 6. Industry-level Relative TFPs

	1995		**2005**		**2014**	
Industry	**TFPQ1**	**TFPQ2**	**TFPQ1**	**TFPQ2**	**TFPQ1**	**TFPQ2**
Food-To.	34.79	37.08	36.85	57.04	1	1
Paper	10.89	17.56	14.00	18.96	10.29	14.15
Chem	52.34	67.07	64.87	63.82	7.61	7.75
Metal	3.08	5.08	2.85	8.04	4.01	4.37
Mach.	1	1	9.45	9.20	9.86	11.12
Elect	3.13	3.15	1	1	2.79	2.83
Trans.Eq	54.12	53.56	11.65	14.90	36.96	36.96

Table Notes. TFP is computed using equation (43). In every year the industry with the lowest TFP is chosen as the base-industry and assigned with a value of $TFP = 1$. For the remaining industries we report industry TFPs relative to this base industry.

Table 7a. Distribution of lnTFPQ1

Industry	1995			2005			2014		
	Mean	S. Dev	# Obs	Mean	S. Dev	# Obs	Mean	S. Dev	# Obs
Food-To.	23.84	1.86	23	24.44	1.51	15	23.70	2.00	36
Paper	20.28	1.23	32	21.03	1.07	18	20.89	1.01	29
Chem	20.53	2.22	64	20.82	2.49	64	19.73	3.44	103
Metal	19.27	0.864	14	19.19	1.71	13	19.65	1.59	23
Mach.	19.40	3.21	10	19.47	2.23	22	20.68	1.55	25
Elect	18.77	2.17	24	18.52	2.97	22	19.09	1.56	34
Trans.Eq	22.90	2.15	13	21.21	3.24	20	22.05	2.10	25

Table Notes. Physical-productivity measure TFPQ1 is computed using equation (38). Industry Mean and Standard Deviations (S. Dev) are cross-sectional statistics for every industry in a given year.

Table 7b. Distribution of lnTFPR1

Industry	1995			2005			2014		
	Mean	S. Dev	# Obs	Mean	S. Dev	# Obs	Mean	S. Dev	# Obs
Food-To.	12.83	0.787	23	12.68	0.686	15	12.81	1.05	36
Paper	9.98	0.561	32	10.51	0.606	18	10.47	0.548	29
Chem	10.24	0.652	64	10.48	1.20	64	10.34	1.59	103
Metal	8.59	0.431	14	8.43	0.856	13	8.86	0.897	23
Mach.	9.99	1.37	10	10.33	0.768	22	10.92	0.710	25
Elect	9.10	0.758	24	8.93	1.46	22	9.23	0.769	34
Trans.Eq	11.45	0.565	13	10.89	1.25	20	11.26	0.791	25

Table Notes. Revenue-productivity measure TFPR1 is computed using equation (39).

Table 7c. Distribution of lnTFPR2

	1995			2005			2014		
Industry	**Mean**	**S. Dev**	**# Obs**	**Mean**	**S. Dev**	**# Obs**	**Mean**	**S. Dev**	**# Obs**
Food-To.	13.30	0.772	23	13.15	0.686	15	13.26	1.03	36
Paper	11.33	0.528	32	11.55	0.645	18	11.48	0.628	29
Chem	11.77	0.966	64	11.96	1.23	64	11.50	1.83	103
Metal	9.41	0.313	14	9.86	0.675	13	10.03	0.551	23
Mach.	10.61	1.47	10	11.26	0.795	22	11.87	0.450	25
Elect	9.74	0.909	24	9.76	1.38	22	9.79	0.567	34
Trans.Eq	12.20	0.700	13	11.78	1.35	20	12.16	0.820	25

Table Notes. Revenue-productivity measure TFPR2 is computed using equation (41).

Table 8a. Distribution of η_K

Industry	1995 Mean	1995 S. Dev	1995 # Obs	2005 Mean	2005 S. Dev	2005 # Obs	2014 Mean	2014 S. Dev	2014 # Obs
Food-To.	-0.103	0.390	24	0.355	1.19	17	0.110	0.153	37
Paper	-0.032	0.177	34	0.081	0.158	19	0.097	0.144	29
Chem	-0.015	0.264	75	0.065	0.195	75	0.066	0.532	147
Metal	0.046	0.131	14	0.050	0.292	14	0.061	0.283	27
Mach.	-0.190	0.397	16	0.184	0.398	22	0.059	0.267	36
Elect	-0.087	0.349	31	0.117	0.390	26	0.044	0.276	44
Trans.Eq	-0.220	0.448	13	0.645	2.57	20	0.111	0.253	27

Table Notes. Capital distortion η_K is backed out using equation (34).

Table 8b. Distribution of η_Y

Industry	1995 Mean	1995 S. Dev	1995 # Obs	2005 Mean	2005 S. Dev	2005 # Obs	2014 Mean	2014 S. Dev	2014 # Obs
Food-To.	-0.030	1.48	24	-0.128	0.541	17	-0.438	1.92	37
Paper	-0.590	1.21	34	-0.305	0.623	19	-0.458	0.851	29
Chem	-0.969	2.51	72	-1.44	5.37	70	-30.27	204.00	115
Metal	-0.695	0.696	14	-0.459	0.745	15	-0.356	0.795	27
Mach.	-8.82	33.53	14	-0.537	1.31	22	-0.455	2.34	35
Elect	-0.513	3.38	31	-2.63	11.68	25	-0.203	0.737	39
Trans.Eq	0.096	0.468	13	-3.20	11.71	20	0.004	0.650	28

Table Notes. Output distortion η_Y is backed out using equation (31).

Table 8c. Distribution of ϕ

Industry	1995 Mean	1995 S. Dev	1995 # Obs	2005 Mean	2005 S. Dev	2005 # Obs	2014 Mean	2014 S. Dev	2014 # Obs
Food-To.	-0.954	0.208	24	-0.999	0.000	17	-0.210	4.79	37
Paper	-0.956	0.162	34	-0.927	0.160	19	-0.922	0.138	29
Chem	-0.932	0.289	76	-0.480	3.55	76	1.45	7.20	150
Metal	-0.915	0.099	14	-0.971	0.020	15	-0.640	1.30	27
Mach.	1.63	7.83	16	-0.201	3.60	22	-.847	0.564	36
Elect	0.557	1.11	31	1.15	6.60	27	.723	4.88	44
Trans.Eq	1.84	8.61	13	-0.976	0.081	20	-0.163	4.20	28

Table Notes. Technique distortion ϕ is backed out using equation (33).

Table 8d. Distribution of $\ln(\hat{z}) = TFPQ2$

Industry	1995 Mean	1995 S. Dev	1995 # Obs	2005 Mean	2005 S. Dev	2005 # Obs	2014 Mean	2014 S. Dev	2014 # Obs
Food-To.	24.30	1.84	23	24.90	1.51	15	24.15	2.01	36
Paper	21.63	1.16	32	22.07	1.52	18	21.90	1.38	29
Chem	22.07	2.73	64	22.29	2.88	64	20.89	3.98	103
Metal	20.10	1.11	14	20.62	1.84	13	20.81	1.55	23
Mach.	20.02	3.31	10	20.40	2.33	22	21.63	1.48	25
Elect	19.41	2.17	24	19.36	3.07	22	19.65	1.77	34
Trans.Eq	23.65	2.38	13	22.10	3.41	20	22.95	2.32	25

Table Notes. Augmented technology frontier $\hat{z}$ is backed out using equation (35), where $TFPQ2 \equiv \hat{z}$.

Table 9a. Setting $\eta_K = 0$ with TFPQ1

	1995	2005	2014
Industry	$\Delta\, TFP$	$\Delta\, TFP$	$\Delta\, TFP$
Food-To.	1.012	0.979	1.000
Paper	0.993	1.002	1.007
Chem	1.004	1.000	1.005
Metal	0.989	0.984	1.016
Mach.	1.023	0.996	1.006
Elect	1.032	1.021	1.034
Trans.Eq	1.042	0.940	1.004

Table 9b. Setting $\eta_Y = 0$ with TFPQ1

	1995	2005	2014
Industry	$\Delta\, TFP$	$\Delta\, TFP$	$\Delta\, TFP$
Food-To.	1.242	1.109	50.667
Paper	1.420	1.002	1.193
Chem	1.442	2.611	30.908
Metal	1.060	1.128	1.062
Mach.	11.164	1.992	1.754
Elect	1.845	8.264	1.473
Trans.Eq	1.014	3.716	1.527

Table Notes. Tables 9a-b present counterfactual experiments, where $\eta_K = 0$ (9a) or $\eta_Y = 0$ (9b) is set for all firms and the resulting counterfactual TFPs are computed. The reported $\Delta\, TFP$ is the ratio between the counterfactual TFP and the benchmark TFP. $\Delta TFP > 1$ indicates an expansion in the industry-TFP after the removal of the distortions, whereas $\Delta TFP < 1$ implies a contraction.

Table 9c. Setting $\phi = 0$ with TFPQ1

	1995	2005	2014
Industry	$\Delta\, TFP$	$\Delta\, TFP$	$\Delta\, TFP$
Food-To.	1.626	1.592	1.577
Paper	5.287	9.730	9.208
Chem	9.346	9.362	10.050
Metal	3.768	14.044	7.996
Mach.	3.089	3.106	3.526
Elect	1.642	2.925	5.747
Trans.Eq	2.677	2.817	2.848

Table 9d. Setting $\phi = 0$ with TFPQ2

	1995	2005	2014
Industry	$\Delta\, TFP$	$\Delta\, TFP$	$\Delta\, TFP$
Food-To.	1.486	1.000	1.577
Paper	3.193	6.984	6.694
Chem	7.105	9.249	9.860
Metal	2.229	4.845	7.344
Mach.	3.009	3.102	3.122
Elect	1.587	2.843	5.662
Trans.Eq	2.635	2.140	2.847

Table Notes. Tables 9c-d present counterfactual experiments, where $\phi = 0$ with TFPQ1 (9a) or $\phi = 0$ with TFPQ2 (9b) is set for all firms and the resulting counterfactual TFPs are computed.

Table 9e. Setting $\eta_K = 0$ with TFPQ1

For $\rho = -0.15$ in all industries

	1995	**2005**	**2014**
Industry	$\Delta\, TFP$	$\Delta\, TFP$	$\Delta\, TFP$
Food-To.	1.012	0.979	1.000
Paper	0.993	1.001	0.999
Chem	1.003	0.997	1.007
Metal	0.989	0.987	1.071
Mach.	1.032	0.996	1.007
Elect	1.033	1.027	1.029
Trans.Eq	1.044	0.939	1.005

Table 9f. Setting $\eta_Y = 0$ with TFPQ1

For $\rho = -0.15$ in all industries

	1995	**2005**	**2014**
Industry	$\Delta\, TFP$	$\Delta\, TFP$	$\Delta\, TFP$
Food-To.	1.242	0.979	50.667
Paper	1.264	1.001	0.787
Chem	1.320	0.997	29.130
Metal	0.945	0.987	0.839
Mach.	11.057	0.996	1.801
Elect	1.839	1.027	1.281
Trans.Eq	0.985	0.939	1.488

Table Notes. Tables 9e-f present counterfactual experiments, where in addition to the η_K and η_Y counterfactual ρ gets set equal to 0.15 in each industry, which is the flexibility level of Food-Tobacco industry.

Table 9g. Setting $\phi = 0$ with TFPQ1

For $\rho = -0.15$ in all industries

Industry	**1995** $\Delta\,TFP$	**1995** Contribution of ρ to $\Delta\,TFP$	**2005** $\Delta\,TFP$	**2005** Contribution of ρ to $\Delta\,TFP$	**2014** $\Delta\,TFP$	**2014** Contribution of ρ to $\Delta\,TFP$
Food-To.	1.626	-	1.592	-	1.577	-
Paper	1.559	71%	1.545	84%	1.565	83%
Chem	1.498	84%	1.478	84%	1.496	85%
Metal	1.990	47%	1.955	86%	1.988	75%
Mach.	1.615	48%	1.596	49%	1.563	56%
Elect	1.985	-21%	1.808	38%	1.915	67%
Trans.Eq	1.642	39%	1.698	39%	1.705	40%

Table 9h. Setting $\phi = 0$ with TFPQ1

For $\rho = -0.15$ in all industries

Industry	**1995** $\Delta\,TFP$	**1995** Contribution of ρ to $\Delta\,TFP$	**2005** $\Delta\,TFP$	**2005** Contribution of ρ to $\Delta\,TFP$	**2014** $\Delta\,TFP$	**2014** Contribution of ρ to $\Delta\,TFP$
Food-To.	1.486	-	1	-	1.577	-
Paper	1.389	57%	1.308	81%	1.269	81%
Chem	1.481	79%	1.475	84%	1.470	85%
Metal	1.029	54%	1	89%	1.987	73%
Mach.	1.588	47%	1.595	49%	1.563	50%
Elect	1.976	-25%	1.767	38%	1.848	67%
Trans.Eq	1.615	39%	1.356	37%	1.704	40%

Table Notes. Tables 9g-h present counterfactual experiments, where in addition to the ϕ counterfactual ρ gets set equal to 0.15 in each industry. In "Contribution of ρ to $\Delta\ TFP$" column, a positive (negative) percentage illustrates by what percentage the original gains from setting $\phi = 0$ reported in Table 9c would contract (expand) if the industry's flexibility equaled 0.15 instead of its original level reported in Table 2.

Table 10a. Setting $\eta_K = 0$ with Neo-classical Production

	1995	**2005**	**2014**
Industry	$\Delta\, TFP$	$\Delta\, TFP$	$\Delta\, TFP$
Food-To.	1.017	0.975	1.000
Paper	0.995	1.001	0.994
Chem	1.003	0.998	1.006
Metal	0.990	0.988	1.118
Mach.	1.043	0.996	1.008
Elect	1.037	1.049	1.020
Trans.Eq	1.048	0.939	1.005

Table 10b. Setting $\eta_Y = 0$ with Neo-classical Production

	1995	**2005**	**2014**
Industry	$\Delta\, TFP$	$\Delta\, TFP$	$\Delta\, TFP$
Food-To.	1.807	1.624	71.520
Paper	2.724	2.639	3.029
Chem	6.889	14.179	175.894
Metal	0.389	3.392	0.818
Mach.	15.795	2.675	4.040
Elect	0.670	1.615	1.026
Trans.Eq	2.204	8.624	3.651

Table Notes. Tables 10a-b present counterfactual experiments, where – instead of the staged-decision making production with techniques choice – a Neo-classical production framework is used with $\hat{z} \equiv TFPQ$.

Table 11a. Misallocation Counterfactuals with $\sigma = 2$ (Year 2014)

Industry	$\Delta\, TFP$ **from** $\eta_K = 0$	$\Delta\, TFP$ **from** $\eta_Y = 0$	$\Delta\, TFP$ **from** $\phi = 0$ **(TFPQ1)**	$\Delta\, TFP$ **from** $\phi = 0$ **(TFPQ2)**
Food-To.	1.000	50.064	1.577	1.577
Paper	1.007	1.123	7.110	5.169
Chem	1.005	29.266	9.778	9.592
Metal	1.016	1.014	5.825	5.350
Mach.	1.006	1.718	3.271	2.897
Elect	1.034	1.381	4.011	3.952
Trans.Eq	1.000	1.563	2.838	2.836

Table 11b. Misallocation Counterfactuals with $\sigma = 4$ (Year 2014)

Industry	$\Delta\, TFP$ **from** $\eta_K = 0$	$\Delta\, TFP$ **from** $\eta_Y = 0$	$\Delta\, TFP$ **from** $\phi = 0$ **(TFPQ1)**	$\Delta\, TFP$ **from** $\phi = 0$ **(TFPQ2)**
Food-To.	1.000	51.854	1.577	1.577
Paper	1.008	1.254	10.629	7.728
Chem	1.006	32.231	10.183	9.989
Metal	1.017	1.124	10.572	9.710
Mach.	1.006	1.801	3.865	3.423
Elect	1.035	1.556	7.086	6.981
Trans.Eq	1.008	1.484	2.853	2.852

Table 12a. Misallocation Counterfactuals with $r = 1.07$ (Year 2014)

Industry	$\Delta\, TFP$ from $\eta_K = 0$	$\Delta\, TFP$ from $\eta_Y = 0$	$\Delta\, TFP$ from $\phi = 0$ (TFPQ1)	$\Delta\, TFP$ from $\phi = 0$ (TFPQ2)
Food-To.	1.000	51.689	1.577	1.577
Paper	1.007	1.188	9.058	6.661
Chem	1.005	31.461	10.042	9.847
Metal	1.016	1.062	7.913	7.280
Mach.	1.006	1.757	3.431	3.060
Elect	1.034	1.470	5.706	5.615
Trans.Eq	1.004	1.545	2.847	2.847

Table 12b. Misallocation Counterfactuals with $r = 1.13$ (Year 2014)

Industry	$\Delta\, TFP$ from $\eta_K = 0$	$\Delta\, TFP$ from $\eta_Y = 0$	$\Delta\, TFP$ from $\phi = 0$ (TFPQ1)	$\Delta\, TFP$ from $\phi = 0$ (TFPQ2)
Food-To.	1.000	49.686	1.577	1.575
Paper	1.007	1.197	9.361	6.729
Chem	1.006	30.380	10.058	9.871
Metal	1.017	1.062	8.080	7.409
Mach.	1.006	1.752	3.620	3.184
Elect	1.034	1.476	5.790	5.711
Trans.Eq	1.004	1.510	2.849	2.845

Table 13a. Misallocation Counterfactuals with constrained TFPR1-dispersion (Year 2014)

Industry	$\Delta\, TFP$ **from** $\eta_K = 0$	$\Delta\, TFP$ **from** $\eta_Y = 0$	$\Delta\, TFP$ **from** $\phi = 0$ **(TFPQ1)**	$\Delta\, TFP$ **from** $\phi = 0$ **(TFPQ2)**	**% Bench-Sample**
Food-To.	1.000	50.667	1.577	1.577	83%
Paper	1.007	1.193	9.208	6.694	89%
Chem	1.005	30.908	10.050	9.860	90%
Metal	1.016	1.062	7.996	7.344	91%
Mach.	1.006	1.754	3.526	3.122	92%
Elect	1.034	1.4734	5.747	5.662	85%
Trans.Eq	1.004	1.527	2.848	2.847	92%

Table 13b. Misallocation Counterfactuals with constrained TFPR2-dispersion (Year 2014)

Industry	$\Delta\, TFP$ **from** $\eta_K = 0$	$\Delta\, TFP$ **from** $\eta_Y = 0$	$\Delta\, TFP$ **from** $\phi = 0$ **(TFPQ1)**	$\Delta\, TFP$ **from** $\phi = 0$ **(TFPQ2)**	**% Bench-Sample**
Food-To.	1.000	50.667	1.577	1.577	80%
Paper	1.007	1.193	9.208	6.694	89%
Chem	1.005	30.908	10.050	9.860	88%
Metal	1.016	1.062	7.996	7.344	86%
Mach.	1.006	1.754	3.526	3.122	80%
Elect	1.034	1.473	5.747	5.662	82%
Trans.Eq	1.004	1.527	2.848	2.847	88%

Table Notes. In the quantitative experiments of Table 13a (13b) we leave out any firm whose TFPR1 (TFPR2) is not within 1.5 standard deviation of the mean TFPR1 (TFPR2). The column Bench-Sample reports the size of the constrained sample relative to the size of the original sample – after leaving out the outliers.

Table 14a. Misallocation Counterfactuals with 15% larger TC of Capital (Year 2014)

Industry	$\Delta\, TFP$ **from** $\eta_K = 0$	$\Delta\, TFP$ **from** $\eta_Y = 0$	$\Delta\, TFP$ **from** $\phi = 0$ **(TFPQ1)**	$\Delta\, TFP$ **from** $\phi = 0$ **(TFPQ2)**
Food-To.	1.000	45.168	1.577	1.556
Paper	1.007	1.212	10.082	6.834
Chem	1.006	28.111	10.096	9.942
Metal	1.016	1.061	8.507	7.540
Mach.	1.006	1.737	4.032	3.411
Elect	1.034	1.496	6.051	6.005
Trans.Eq	1.004	1.423	2.852	2.822

Table 14b. Misallocation Counterfactuals with 15% smaller TC of Capital (Year 2014)

Industry	$\Delta\, TFP$ **from** $\eta_K = 0$	$\Delta\, TFP$ **from** $\eta_Y = 0$	$\Delta\, TFP$ **from** $\phi = 0$ **(TFPQ1)**	$\Delta\, TFP$ **from** $\phi = 0$ **(TFPQ2)**
Food-To.	1.000	57.718	1.577	1.577
Paper	1.007	1.173	8.386	6.549
Chem	1.005	34.599	9.990	9.753
Metal	1.016	1.065	7.371	6.999
Mach.	1.006	1.776	2.946	2.723
Elect	1.034	1.452	5.499	5.347
Trans.Eq	1.003	1.662	2.844	2.843

Table Notes. In the quantitative experiments of Table 14a (14b) we raise (lower) the measured total cost of capital for all firms in our analysis by 15%.

Table 15a. India: Distributional Properties of Firm-Variables

Variable Name	Mean	Std. Dev.	Min	Max	# Obs.
ln(Labor)	6.63	6.63	0	11.79	16977
ln(Capital)	19.92	2.00	8.69	28.42	67828
ln(Total Labor Cost)	17.44	2.45	6.90	26.27	68561
ln(Total Capital Cost)	19.75	2.01	7.60	28.47	63520
ln(Total Revenue)	20.35	2.25	6.90	29.21	69837

Table 15b. China: Distributional Properties of Firm-Variables

Variable Name	Mean	Std. Dev.	Min	Max	# Obs.
ln(Labor)	7.57	1.50	3.04	13.22	3448
ln(Capital)	19.68	1.23	13.15	28.29	59039
ln(Total Labor Cost)	18.51	1.78	8.29	25.51	4576
ln(Total Capital Cost)	19.80	1.62	10.89	28.43	54759
ln(Total Revenue)	20.49	1.27	6.90	28.45	64684

Table Notes. Firm-level averages in Tables 15a-b are from Compustat-Global Fundamentals Annual for the years between 1995-2014 – from firms operational in manufacturing industry-clusters presented in Table 1.

Table 16a. India: Setting $\eta_K = 0$ and $\eta_Y = 0$

	$\eta_K = 0$		$\eta_Y = 0$	
	2005	**2014**	**2005**	**2014**
Industry	$\Delta\, TFP$	$\Delta\, TFP$	$\Delta\, TFP$	$\Delta\, TFP$
Food-To.	1.043	1.007	6.518	6.103
Paper	1.020	0.991	4.124	4.890
Chem	1.016	0.648	7.984	1.561
Metal	0.989	0.899	2.435	66.260
Mach.	0.997	1.009	2.895	2.885
Elect	0.978	0.998	1.702	16.003
Trans.Eq	1.000	1.016	1.464	4.715

Table 16b. India: Setting $\phi = 0$

	$\phi = 0$ **with** $TFPQ1$		$\phi = 0$ **with** $TFPQ2$	
	2005	**2014**	**2005**	**2014**
Industry	$\Delta\, TFP$	$\Delta\, TFP$	$\Delta\, TFP$	$\Delta\, TFP$
Food-To.	1.506	1.503	1.497	1.501
Paper	10.497	14.494	2.475	13.399
Chem	9.903	12.978	4.405	8.966
Metal	11.416	26.939	9.705	18.070
Mach.	7.011	6.758	1.940	6.379
Elect	7.675	9.995	4.760	4.976
Trans.Eq	2.608	2.604	1.000	2.061

Table 17a. China: Setting $\eta_K = 0$ and $\eta_Y = 0$

	$\eta_K = 0$		$\eta_Y = 0$	
	2005	**2014**	**2005**	**2014**
Industry	$\Delta\, TFP$	$\Delta\, TFP$	$\Delta\, TFP$	$\Delta\, TFP$
Food-To.	N/A	0.989	N/A	1.469
Paper	N/A	1.030	N/A	2.585
Chem	1.003	0.990	2.520	8.607
Metal	0.976	0.991	2.130	4.008
Mach.	1.037	0.946	1.724	2.026
Elect	1.047	1.003	2.117	3.239
Trans.Eq	1.018	0.993	0.803	1.886

Table 17b. China: Setting $\phi = 0$

	$\phi = 0$ **with** $TFPQ1$		$\phi = 0$ **with** $TFPQ2$	
	2005	**2014**	**2005**	**2014**
Industry	$\Delta\, TFP$	$\Delta\, TFP$	$\Delta\, TFP$	$\Delta\, TFP$
Food-To.	N/A	1.538	N/A	1.000
Paper	N/A	7.733	N/A	2.081
Chem	8.166	9.921	0.838	3.008
Metal	10.939	16.274	6.044	2.912
Mach.	9.703	4.108	6.793	2.240
Elect	1.436	10.166	1.412	8.027
Trans.Eq	2.681	2.574	1.284	1.727

Appendix

In this Appendix, we provide detailed mathematical derivations and proofs of various Lemmas and Propositions.

Benchmark Step-2 Solution: The Cost Minimizing $K-L$

The second-step is the standard neoclassical cost minimization problem presented at (4). Denoting the Lagrange multiplier associated with constraint by μ_1, solving for μ_1 will provide the marginal cost of producing one extra unit of output. First order conditions with respect to K and L are derived as the following

$$\begin{aligned} K \quad &: \quad r = \mu_1 \lambda a_K^{\rho} K^{\rho-1} [(a_K K)^{\rho} + (a_L L)^{\rho}]^{\frac{1-\rho}{\rho}} \\ \Rightarrow \quad & \quad K = \mu_1^{\frac{1}{1-\rho}} r^{\frac{-1}{1-\rho}} \lambda^{\frac{1}{1-\rho}} a_K^{\frac{\rho}{1-\rho}} Y; \qquad (49) \\ L \quad &: \quad w = \mu_1 (1-\lambda) a_L^{\rho} L^{\rho-1} [(a_K K)^{\rho} + (a_L L)^{\rho}]^{\frac{1-\rho}{\rho}} \\ \Rightarrow \quad & \quad L = \mu_1^{\frac{1}{1-\rho}} w^{\frac{-1}{1-\rho}} (1-\lambda)^{\frac{1}{1-\rho}} a_L^{\frac{\rho}{1-\rho}} Y. \qquad (50) \end{aligned}$$

Putting (49) and (50) together yields to the K/L ratio at (6). Plugging K and L from (49) and (50) into the constraint at (4) and solving for μ_1 provides the unit cost of production that we presented at (7).

Benchmark Step-1 Solution: The optimized a_K-a_L

The first-step cost minimization problem is stated at (5). Denoting the lagrange multiplier associated with the constraint by μ_2, we can derive the first order conditions with respect to a_K and a_L

$$a_K \quad : \quad r^{\frac{\rho}{\rho-1}} \lambda^{\frac{1}{1-\rho}} a_K^{-\frac{\rho}{\rho-1}-1} \left[\left(\frac{r}{a_K}\right)^{\frac{\rho}{\rho-1}} \lambda^{\frac{1}{1-\rho}} + \left(\frac{w}{a_L}\right)^{\frac{\rho}{\rho-1}} (1-\lambda)^{\frac{1}{1-\rho}} \right]^{\frac{\rho-1}{\rho}-1} = \mu_2 \alpha a_K^{\alpha-1} a_L^{1-\alpha}, \qquad (51)$$

$$a_L \quad : \quad w^{\frac{\rho}{\rho-1}} (1\text{-}\lambda)^{\frac{1}{1-\rho}} a_L^{-\frac{\rho}{\rho-1}-1} \left[\left(\frac{r}{a_K}\right)^{\frac{\rho}{\rho-1}} \lambda^{\frac{1}{1-\rho}} + \left(\frac{w}{a_L}\right)^{\frac{\rho}{\rho-1}} (1\text{-}\lambda)^{\frac{1}{1-\rho}} \right]^{\frac{\rho-1}{\rho}-1} = \mu_2 (1\text{-}\alpha) a_K^{\alpha} a_L^{-\alpha}. \qquad (52)$$

Solving (51) and (52) together provide us with the optimized a_K/a_L ratio at (8). Plugging (8) in (6) solves for the optimized K/L ratio as a function of model parameters α and λ; and factor prices r and w as we expressed at (9). In order to determine the levels of a_K and a_L as functions of z, w/r, α and ρ, we plug (8) in $H(a_K, a_L)$ and obtain the expressions at (10) and (11). Plugging a_K and a_L in $\tilde{c}(.)$ provides

$$c(w,r) = \frac{1}{z} r^{\alpha} w^{1-\alpha} \left[\lambda^{\alpha}(1-\lambda)^{1-\alpha}\right]^{-\frac{1}{\rho}} \left[\left(\frac{\alpha}{1-\alpha}\right)^{1-\alpha} + \left(\frac{1-\alpha}{\alpha}\right)^{\alpha} \right]^{\frac{\rho-1}{\rho}}.$$

Finally, putting the related terms together yields the unit cost expression at (12).

Proof of Proposition 3.1

In order to evaluate the optimality of an interior solution we need to consider two relevant cases, (i) $\rho \in (-\infty, 0)$ and (ii) $\rho \in (0,1)$, and check whether the unit cost function function at (12) is indeed minimized for $a_K^* - a_L^*$ that we derived at (10) and (11).

Case-i: $\rho \in (-\infty, 0)$.

We perturb the $a_K - a_L$ choice from $a_K^* - a_L^*$ we just derived by ϵ – while keeping the firm on the same technology menu dictated by its technology frontier z – and investigate whether the optimal ϵ that minimizes the unit cost is $\epsilon = 0$.

Specifically, suppose that the firm operates with a capital intensity of $\hat{a}_K = (1+\epsilon)^{1-\alpha} a_K^*$ – with $-1 < \epsilon$ finite – instead of a_K^*. Since the firm is bound by the technology frontier z, this implies that $\hat{a}_L = (1+\epsilon)^{-\alpha} a_L^*$ so that $(\hat{a}_K)^\alpha (\hat{a}_L)^{1-\alpha} = z$. Given $\hat{a}_K - \hat{a}_L$, the unit cost of production becomes

$$c(w, r; \epsilon) = \frac{1}{z} \left(\left(\frac{\alpha}{\lambda} \right)^{\frac{1}{\rho}} \frac{r}{\alpha} \right)^{\alpha} \left(\left(\frac{1-\alpha}{1-\lambda} \right)^{\frac{1}{\rho}} \frac{w}{1-\alpha} \right)^{1-\alpha} \underbrace{(1+\epsilon)^{\alpha} \left(1 + \alpha \left((1+\epsilon)^{\frac{\rho}{1-\rho}} - 1 \right) \right)^{\frac{\rho-1}{\rho}}}_{\equiv \Omega(\epsilon)}. \tag{53}$$

Then,

$$\frac{\partial c}{\partial \epsilon} = \frac{c}{\Omega(\epsilon)} \left[\alpha (1+\epsilon)^{\alpha-1} \left(1 + \alpha \left((1+\epsilon)^{\frac{\rho}{1-\rho}} - 1 \right) \right)^{\frac{\rho-1}{\rho}} - \alpha (1+\epsilon)^{\alpha + \frac{2\rho-1}{1-\rho}} \left(1 + \alpha \left((1+\epsilon)^{\frac{\rho}{1-\rho}} - 1 \right) \right)^{\frac{-1}{\rho}} \right]. \tag{54}$$

We note that $\frac{\partial c}{\partial \epsilon} = 0$ if and only if $\epsilon = 0$. Next we check whether $\epsilon = 0$ constitutes a global minimum or a global maximum (and if the latter turns out to be the case the optimal $a_K - a_L$ choice would be given by a corner solution and not by (10) and (11)). There are two cases to consider: $\epsilon > 0$ and $\epsilon < 0$. We can easily note that $\epsilon = 0$ constitutes a global minimum for the unit cost function if and only if

$$\text{for } \epsilon > 0, \quad \frac{\partial c}{\partial \epsilon} > 0, \tag{55}$$

$$\text{for } \epsilon < 0, \quad \frac{\partial c}{\partial \epsilon} < 0. \tag{56}$$

Using (54), we can see that

$$\text{for } \epsilon > 0, \quad \frac{\partial c}{\partial \epsilon} > 0 \ \text{ if } \ (1-\alpha) > (1-\alpha)(1+\epsilon)^{\frac{\rho}{1-\rho}}, \tag{57}$$

$$\text{for } \epsilon < 0, \quad \frac{\partial c}{\partial \epsilon} < 0 \ \text{ if } \ (1-\alpha) < (1-\alpha)(1+\epsilon)^{\frac{\rho}{1-\rho}}. \tag{58}$$

Both conditions hold, since $0 < \alpha < 1$ and $\rho < 0$. Hence, choosing $a_K - a_L$ interiorly as (10) and (11) in the second-stage minimizes the firm's unit cost of production as long as $\rho < 0$.

Case-ii: $\rho \in (0, 1)$.

Expressions (10)-(12) fully remain for the case of $1 > \rho > 0$; and therefore, we do not repeat them. The optimality conditions (54)-(58) also remain. What changes compared to the case-i is that with $\rho > 0$ the conditions of optimality become

$$\text{for } \epsilon > 0, \ (1-\alpha) < (1-\alpha)(1+\epsilon)^{\frac{\rho}{1-\rho}}, \tag{59}$$

$$\text{for } \epsilon < 0, \ (1-\alpha) > (1-\alpha)(1+\epsilon)^{\frac{\rho}{1-\rho}}. \tag{60}$$

Therefore, given (57)-(58), in industries with $\rho \in (0,1)$ the optimal (a_K^*, a_L^*) combination is at a corner. Hence, depending on the parameter constellations of the economy the optimal a_K^* and a_L^* are given by

$$a_K^* = \underline{a}_K, \tag{61}$$
$$a_L^* = \left(z\underline{a}_K^{-\alpha}\right)^{\frac{1}{1-\alpha}}, \tag{62}$$

or,

$$a_K^* = \left(z\underline{a}_L^{\alpha-1}\right)^{\frac{1}{\alpha}}, \tag{63}$$
$$a_L^* = \underline{a}_L. \tag{64}$$

Proof of Proposition 3.2

We re-write the unit cost function as

$$c(w,r) = \frac{1}{z} r^{\alpha} w^{1-\alpha} \left[\underbrace{\left(\lambda^{\alpha}(1-\lambda)^{1-\alpha}\right)^{-1}}_{\Omega_1}\right]^{\frac{1}{\rho}} \left[\underbrace{\alpha^{\alpha}(1-\alpha)^{1-\alpha}}_{\Omega_2}\right]^{\frac{1-\rho}{\rho}} \tag{65}$$

The first term inside the square brackets (Ω_1) is greater than 1 whereas the second term (Ω_2) is smaller than 1. Therefore, the impact of more flexibility on cost of production depends on λ and α. Specifically, if

$$\lambda^{\alpha}(1-\lambda)^{1-\alpha} < \alpha^{\alpha}(1-\alpha)^{1-\alpha} \tag{66}$$

then more flexibility is desirable. In order to see the parameter conditions for which the (66) holds; note that

$$\arg\max_{\lambda}\ \lambda^{\alpha}(1-\lambda)^{1-\alpha} = \alpha,$$

which implies that the highest value the LHS of (66) could attain equals to $\alpha^{\alpha}(1-\alpha)^{1-\alpha}$. Therefore, $\lambda^{\alpha}(1-\lambda)^{1-\alpha} \leq \alpha^{\alpha}(1-\alpha)^{1-\alpha}$ for all $\lambda, \alpha \in [0,1]$.

Derivation of Unit Cost of Production with Distortions

Recursive solution to firm's staged decision making process is as follows.

$$\textbf{Stage-4.} \qquad \max_{p}\ (1-\eta_Y)pY^d(p) - c(\phi,\eta)Y^d(p) = \left[(1-\eta_Y)p - c(\phi,\eta)\right]Y^d(p)$$
$$s.t. \qquad Y^d(p) = \left(\frac{p}{P}\right)^{-\sigma} Y_J.$$

First-order conditions are

$$\begin{aligned}(1-\eta_Y)Y^d(p) &= \sigma\left[(1-\eta_Y)p - c(\phi,\eta)\right]Y^d(p)/p,\\ (1-\eta_Y)p &= \sigma\left[(1-\eta_Y)p - c(\phi,\eta)\right],\\ p &= \frac{\sigma}{\sigma-1}\frac{c}{1-\eta_Y},\end{aligned}$$

which provides the pricing function.

$$\textbf{Stage-3.} \quad \min_{K,L} \; r(1+\eta_K)K + wL$$
$$s.t. \quad Y = [\lambda(a_K K)^\rho + (1-\lambda)(a_L L)^\rho]^{\frac{1}{\rho}}.$$

First-order conditions are

$$\begin{aligned}
(1+\eta_K)r &= MPK = \mu \frac{\lambda (a_K K)^\rho}{\lambda(a_K K)^\rho + (1-\lambda)(a_L L)^\rho} \frac{Y}{K} \\
w &= MPL = \mu \frac{(1-\lambda)(a_L L)^\rho}{\lambda(a_K K)^\rho + (1-\lambda)(a_L L)^\rho} \frac{Y}{L} \\
\frac{w}{(1+\eta_K)r} &= \frac{\mu \frac{(1-\lambda)(a_L L)^\rho}{\lambda(a_K K)^\rho + (1-\lambda)(a_L L)^\rho} \frac{Y}{L}}{\mu \frac{\lambda(a_K K)^\rho}{\lambda(a_K K)^\rho + (1-\lambda)(a_L L)^\rho} \frac{Y}{K}} = \frac{(1-\lambda)(a_L L)^\rho K}{\lambda (a_K K)^\rho L} = \frac{1-\lambda}{\lambda} \left(\frac{a_L}{a_K}\right)^\rho \left(\frac{K}{L}\right)^{1-\rho} \\
(1+\eta_K)rK + wL &= \mu \frac{\lambda (a_K K)^\rho + (1-\lambda)(a_L L)^\rho}{\lambda(a_K K)^\rho + (1-\lambda)(a_L L)^\rho} Y, \text{ or, } c = \mu
\end{aligned}$$

We can express K/L ratio and the unit cost as a function of (a_K, a_L) as follows.

$$\frac{K}{L} = \left(\frac{w}{(1+\eta_K)r}\right)^{\frac{1}{1-\rho}} \left(\frac{\lambda}{1-\lambda}\right)^{\frac{1}{1-\rho}} \left(\frac{a_K}{a_L}\right)^{\frac{\rho}{1-\rho}}$$

$$\begin{aligned}
\tilde{c}(a_K, a_L; r, w) &= \frac{(1+\eta_K)rK + wL}{[\lambda(a_K K)^\rho + (1-\lambda)(a_L L)^\rho]^{\frac{1}{\rho}}} \\
&= \frac{(1+\eta_K)r \left(\frac{w}{(1+\eta_K)r}\right)^{\frac{1}{1-\rho}} \left(\frac{\lambda}{1-\lambda}\right)^{\frac{1}{1-\rho}} \left(\frac{a_K}{a_L}\right)^{\frac{\rho}{1-\rho}} + w}{\left[\lambda \left(a_K \left(\frac{w}{(1+\eta_K)r}\right)^{\frac{1}{1-\rho}} \left(\frac{\lambda}{1-\lambda}\right)^{\frac{1}{1-\rho}} \left(\frac{a_K}{a_L}\right)^{\frac{\rho}{1-\rho}}\right)^\rho + (1-\lambda)(a_L)^\rho\right]^{\frac{1}{\rho}}} \\
&= \frac{\left(\frac{(1+\eta_K)r}{a_K}\right)^{\frac{-\rho}{1-\rho}} (\lambda)^{\frac{1}{1-\rho}} + \left(\frac{w}{a_L}\right)^{\frac{-\rho}{1-\rho}} (1-\lambda)^{\frac{1}{1-\rho}}}{(w)^{\frac{-1}{1-\rho}} (1-\lambda)^{\frac{1}{1-\rho}} (a_L)^{\frac{\rho}{1-\rho}} \left[\lambda \left(a_K \left(\frac{w}{(1+\eta_K)r}\right)^{\frac{1}{1-\rho}} \left(\frac{\lambda}{1-\lambda}\right)^{\frac{1}{1-\rho}} \left(\frac{a_K}{a_L}\right)^{\frac{\rho}{1-\rho}}\right)^\rho + (1-\lambda)(a_L)^\rho\right]^{\frac{1}{\rho}}} \\
&= \frac{\left(\frac{(1+\eta_K)r}{a_K}\right)^{\frac{-\rho}{1-\rho}} (\lambda)^{\frac{1}{1-\rho}} + \left(\frac{w}{a_L}\right)^{\frac{-\rho}{1-\rho}} (1-\lambda)^{\frac{1}{1-\rho}}}{\left[\lambda \left(\left(\frac{1}{(1+\eta_K)r}\right)^{\frac{1}{1-\rho}} (\lambda)^{\frac{1}{1-\rho}} (a_K)^{\frac{1}{1-\rho}}\right)^\rho + (1-\lambda)((w)^{\frac{-1}{1-\rho}} (1-\lambda)^{\frac{1}{1-\rho}} (a_L)^{\frac{1}{1-\rho}})^\rho\right]^{\frac{1}{\rho}}} \\
&= \left[\left(\frac{(1+\eta_K)r}{a_K}\right)^{\frac{-\rho}{1-\rho}} (\lambda)^{\frac{1}{1-\rho}} + \left(\frac{w}{a_L}\right)^{\frac{-\rho}{1-\rho}} (1-\lambda)^{\frac{1}{1-\rho}}\right]^{\frac{1-\rho}{-\rho}}.
\end{aligned}$$

Stage-2. The *ex ante* unforeseeable distortion (ϕ) to techniques-choice gets determined, which pushes the techniques-combination away from the benchmark chosen in Stage-1. Since we assume that the expected value of ϕ equals zero under unforeseeable mistakes, in Stage-1 the firm chooses techniques optimally:

$$\textbf{Stage-1.} \quad \min_{a_K, a_L} \; \tilde{c}(a_K, a_L; r, w) = \left[\left(\frac{(1+\eta_K)r}{a_K}\right)^{\frac{\rho}{\rho-1}} \lambda^{\frac{1}{1-\rho}} + \left(\frac{w}{a_L}\right)^{\frac{\rho}{\rho-1}} (1-\lambda)^{\frac{1}{1-\rho}}\right]^{\frac{\rho-1}{\rho}}$$
$$s.t. \quad a_K^\alpha a_L^{1-\alpha} = z,$$

yielding *ex ante* optimal a_K^* and a_L^*

$$a_K^* = z\left(\frac{w}{r(1+\eta_K)}\right)^{-(1-\alpha)}\left(\frac{\alpha}{1-\alpha}\right)^{(1-\alpha)\left(\frac{1-\rho}{\rho}\right)}\left(\frac{1-\lambda}{\lambda}\right)^{(1-\alpha)\left(\frac{1}{\rho}\right)},$$
$$a_L^* = z\left(\frac{w}{r(1+\eta_K)}\right)^{\alpha}\left(\frac{\alpha}{1-\alpha}\right)^{-\alpha\left(\frac{1-\rho}{\rho}\right)}\left(\frac{1-\lambda}{\lambda}\right)^{-\alpha\left(\frac{1}{\rho}\right)},$$

and the distorted $\hat{a}_K$ and $\hat{a}_L$ as of Stage-2 then take the form of:

$$\hat{a}_K = z\left(\frac{w}{r(1+\eta_K)}\right)^{-(1-\alpha)}\left(\frac{\alpha}{1-\alpha}\right)^{(1-\alpha)\left(\frac{1-\rho}{\rho}\right)}\left(\frac{1-\lambda}{\lambda}\right)^{(1-\alpha)\left(\frac{1}{\rho}\right)}(1+\phi)^{1-\alpha},$$
$$\hat{a}_L = z\left(\frac{w}{r(1+\eta_K)}\right)^{\alpha}\left(\frac{\alpha}{1-\alpha}\right)^{-\alpha\left(\frac{1-\rho}{\rho}\right)}\left(\frac{1-\lambda}{\lambda}\right)^{-\alpha\left(\frac{1}{\rho}\right)}(1+\phi)^{-\alpha}.$$

Finally, plugging $\hat{a}_K$ and $\hat{a}_L$ into the unit cost function from Stage-2 yields the final form of unit cost of production.

$$\begin{aligned} c &= \frac{((1+\phi)(1+\eta_K)r)^{\alpha}\, w^{1-\alpha}\lambda^{-\alpha\frac{1}{\rho}}\,(1-\lambda)^{-(1-\alpha)\frac{1}{\rho}}\left(\frac{\alpha}{1-\alpha}\right)^{\alpha\left(\frac{1-\rho}{\rho}\right)}}{z}\left[\left(\frac{\alpha}{1-\alpha}\right)(1+\phi)^{\frac{\rho}{1-\rho}}+1\right]^{\frac{\rho-1}{\rho}} \\ &= \frac{((1+\phi)(1+\eta_K)r)^{\alpha}\, w^{1-\alpha}\lambda^{-\alpha\frac{1}{\rho}}\,(1-\lambda)^{-(1-\alpha)\frac{1}{\rho}}\,(\alpha)^{\alpha\frac{1}{\rho}}\,(1-\alpha)^{(1-\alpha)\frac{1}{\rho}}\,\alpha^{-\alpha}\,(1-\alpha)^{\frac{\rho-1}{\rho}-(1-\alpha)}}{z}\cdot \\ &\quad \left[\left(\frac{\alpha}{1-\alpha}\right)(1+\phi)^{\frac{\rho}{1-\rho}}+1\right]^{\frac{\rho-1}{\rho}}, \end{aligned}$$

or,

$$c(\phi;\eta) = \frac{(1+\phi)^{\alpha}}{z}\left(\left(\frac{\alpha}{\lambda}\right)^{\frac{1}{\rho}}\frac{r(1+\eta_K)}{\alpha}\right)^{\alpha}\left(\left(\frac{1-\alpha}{1-\lambda}\right)^{\frac{1}{\rho}}\frac{w}{1-\alpha}\right)^{1-\alpha}\left[1+\alpha\left((1+\phi)^{\frac{\rho}{1-\rho}}-1\right)\right]^{\frac{\rho-1}{\rho}}.$$

Proof of Proposition 4.1

Let us define $\Phi \equiv 1+\phi$. Suppose that $\rho < 0$ and $\phi > 0$. First observe that:

$$\begin{aligned} c &\propto \Phi^{\alpha}\left[1+\alpha\left(\Phi^{\frac{\rho}{1-\rho}}-1\right)\right]^{\frac{1-\rho}{-\rho}} \\ \frac{\partial C}{\partial \Phi} &= \alpha\Phi^{\alpha-1}\left[1+\alpha\left(\Phi^{\frac{\rho}{1-\rho}}-1\right)\right]^{\frac{1-\rho}{-\rho}} - \Phi^{\alpha}\left[1+\alpha\left(\Phi^{\frac{\rho}{1-\rho}}-1\right)\right]^{\frac{1-\rho}{-\rho}-1}\alpha\Phi^{\frac{\rho}{1-\rho}-1} \\ &= \alpha\Phi^{\alpha-1}\left[1+\alpha\left(\Phi^{\frac{\rho}{1-\rho}}-1\right)\right]^{\frac{1-\rho}{-\rho}-1}\left\{\left[1+\alpha\left(\Phi^{\frac{\rho}{1-\rho}}-1\right)\right]-\Phi^{\frac{\rho}{1-\rho}}\right\} \\ &= \alpha\Phi^{\alpha-1}\left[1+\alpha\left(\Phi^{\frac{\rho}{1-\rho}}-1\right)\right]^{\frac{1-\rho}{-\rho}-1}\left\{1-\alpha-(1-\alpha)\,\Phi^{\frac{\rho}{1-\rho}}\right\} \\ &= \alpha\,(1-\alpha)\,\Phi^{\alpha-1}\left[1+\alpha\left(\Phi^{\frac{\rho}{1-\rho}}-1\right)\right]^{\frac{-1}{\rho}}\left(1-\Phi^{\frac{\rho}{1-\rho}}\right) > 0 \text{ for } \Phi > 1 \text{ and } \rho < 0 \end{aligned}$$

And, also observe that:

$$
\begin{aligned}
\frac{\partial^2 c}{\partial\Phi\partial\rho} &\propto \frac{\partial}{\partial\rho}\left[1-\alpha\left(1-\Phi^{\frac{\rho}{1-\rho}}\right)\right]^{\frac{-1}{\rho}}\left(1-\Phi^{\frac{\rho}{1-\rho}}\right) \\
&= \left[1-\alpha\left(1-\Phi^{\frac{\rho}{1-\rho}}\right)\right]^{\frac{-1}{\rho}}\left(1-\Phi^{\frac{\rho}{1-\rho}}\right)\frac{1}{\rho^2}\ln\left(1-\alpha\left(1-\Phi^{\frac{\rho}{1-\rho}}\right)\right) \\
&\quad +\left(\frac{-1}{\rho}\right)\left[1-\alpha\left(1-\Phi^{\frac{\rho}{1-\rho}}\right)\right]^{\frac{-1}{\rho}-1}\alpha\frac{1}{(1-\rho)^2}\ln(\Phi)\left(1-\Phi^{\frac{\rho}{1-\rho}}\right) \\
&\quad -\left[1-\alpha\left(1-\Phi^{\frac{\rho}{1-\rho}}\right)\right]^{\frac{-1}{\rho}}\frac{1}{(1-\rho)^2}\ln(\Phi) \\
&\propto \left(1-\Phi^{\frac{\rho}{1-\rho}}\right)\frac{1}{\rho^2}\ln\left(1-\alpha\left(1-\Phi^{\frac{\rho}{1-\rho}}\right)\right) \\
&\quad -\left\{1-\left(\frac{-1}{\rho}\right)\left[1-\alpha\left(1-\Phi^{\frac{\rho}{1-\rho}}\right)\right]^{-1}\alpha\left(1-\Phi^{\frac{\rho}{1-\rho}}\right)\right\}\frac{1}{(1-\rho)^2}\ln(\Phi) \\
&< 0 \text{ for the case of } \Phi>1 \text{ and } \rho<0 \text{ if}
\end{aligned}
$$

$$
1>\left(\frac{-1}{\rho}\right)\left[1-\alpha\left(1-\Phi^{\frac{\rho}{1-\rho}}\right)\right]^{-1}\alpha\left(1-\Phi^{\frac{\rho}{1-\rho}}\right), \tag{67}
$$

or, if

$$
\alpha\left(1-\Phi^{\frac{\rho}{1-\rho}}\right)<\frac{\rho}{\rho-1}, \tag{68}
$$

since $\left(1-\Phi^{\frac{\rho}{1-\rho}}\right)\frac{1}{\rho^2}\ln\left(1-\alpha\left(1-\Phi^{\frac{\rho}{1-\rho}}\right)\right)<0$ and $\frac{1}{(1-\rho)^2}\ln(\Phi)>0$. Note that (68) is a sufficient condition.

Then we can conclude:

a. if $\frac{1}{\alpha}\frac{\rho}{\rho-1}>1$, no further condition needed;

b. if $\frac{1}{\alpha}\frac{\rho}{\rho-1}<1$, we need:

$$
1-\left(\frac{1}{\Phi}\right)^{\frac{-\rho}{1-\rho}}<\frac{1}{\alpha}\frac{\rho}{\rho-1},
$$

or,

$$
\Phi<\frac{1}{\left(1-\frac{1}{\alpha}\frac{\rho}{\rho-1}\right)^{\frac{\rho-1}{\rho}}},
$$

which is the upper bound $1+\bar{\phi}$. The case of $\rho<0$ and $\phi<0$ produces similar “mirror image” results but no upper bound is needed.

Online Appendix

Table OA1a. Setting $\eta_K = 0$ with TFPQ1 - 1996-2012

	1996	**1998**	**2000**	**2002**	**2004**
Industry	$\Delta\, TFP$	$\Delta\, TFP$	$\Delta\, TFP$	$\Delta\, TFP$	$\Delta\, TFP$
Food-To.	1.017	1.015	1.006	1.000	1.001
Paper	1.002	1.007	1.001	0.995	0.999
Chem	1.004	0.996	0.997	0.983	0.989
Metal	1.014	1.025	0.804	0.974	0.995
Mach.	1.004	0.891	0.968	0.985	0.998
Elect	1.016	0.902	1.044	1.028	0.973
Trans.Eq	1.017	1.004	1.005	1.036	1.000

Table OA1a ctd.

	2006	**2008**	**2010**	**2012**
Industry	$\Delta\, TFP$	$\Delta\, TFP$	$\Delta\, TFP$	$\Delta\, TFP$
Food-To.	1.002	1.003	0.998	0.998
Paper	1.008	0.997	1.004	1.008
Chem	0.996	0.986	0.980	1.010
Metal	0.946	1.014	1.033	1.000
Mach.	1.004	1.002	1.026	1.011
Elect	0.932	0.933	1.002	1.075
Trans.Eq	1.020	1.003	0.987	1.001

Table OA1b. Setting $\eta_Y = 0$ with TFPQ1 - 1996-2012

	1996	**1998**	**2000**	**2002**	**2004**
Industry	$\Delta\, TFP$	$\Delta\, TFP$	$\Delta\, TFP$	$\Delta\, TFP$	$\Delta\, TFP$
Food-To.	0.921	1.461	5.385	1.696	1.763
Paper	1.158	1.815	2.884	1.046	1.022
Chem	2.230	8.856	38.544	4.709	6.846
Metal	1.077	1.045	3.098	1.798	1.316
Mach.	4.326	8.183	4.085	5.392	37.278
Elect	3.742	1.726	2.78	22.152	3.046
Trans.Eq	0.983	0.985	0.953	1.855	1.409

Table OA1b ctd.

	2006	**2008**	**2010**	**2012**
Industry	$\Delta\, TFP$	$\Delta\, TFP$	$\Delta\, TFP$	$\Delta\, TFP$
Food-To.	1.011	1.130	6.779	9.889
Paper	0.994	1.099	1.366	1.197
Chem	3.418	12.163	2.174	106.248
Metal	1.209	1.075	5.811	1.348
Mach.	2.556	2.388	1.060	1.733
Elect	14.217	60.642	4.234	10.724
Trans.Eq	25.626	1.358	1.217	4.651

Table OA1c. Setting $\phi = 0$ with TFPQ1 - 1996-2012

	1996	**1998**	**2000**	**2002**	**2004**
Industry	$\Delta\, TFP$	$\Delta\, TFP$	$\Delta\, TFP$	$\Delta\, TFP$	$\Delta\, TFP$
Food-To.	1.644	1.640	1.636	1.617	1.620
Paper	6.119	16.220	10.816	8.882	9.863
Chem	9.501	9.271	9.399	9.362	9.363
Metal	2.777	3.004	3.381	3.557	14.058
Mach.	2.881	7.178	3.198	3.632	3.042
Elect	1.872	1.641	1.524	12.693	4.469
Trans.Eq	2.709	2.730	2.753	2.811	2.823

Table OA1c ctd.

	2006	**2008**	**2010**	**2012**
Industry	$\Delta\, TFP$	$\Delta\, TFP$	$\Delta\, TFP$	$\Delta\, TFP$
Food-To.	1.593	1.602	1.571	1.578
Paper	7.640	9.397	9.263	8.904
Chem	9.314	9.565	9.626	10.253
Metal	11.849	11.071	11.579	6.885
Mach.	2.964	2.734	2.949	3.075
Elect	2.617	5.576	6.026	5.774
Trans.Eq	2.829	2.805	2.784	2.832

Table OA1d. Setting $\phi = 0$ with TFPQ2 - 1996-2012

	1996	1998	2000	2002	2004
Industry	$\Delta\, TFP$	$\Delta\, TFP$	$\Delta\, TFP$	$\Delta\, TFP$	$\Delta\, TFP$
Food-To.	1.403	1.297	1.343	1.000	1.000
Paper	5.156	11.241	7.685	6.030	7.177
Chem	8.454	8.270	9.397	9.360	9.341
Metal	1.727	3.003	3.042	1.269	4.548
Mach.	2.151	7.164	3.165	3.619	2.726
Elect	1.460	1.551	1.465	12.616	4.381
Trans.Eq	2.706	1.551	2.159	2.790	2.567

Table OA1d ctd.

	2006	2008	2010	2012
Industry	$\Delta\, TFP$	$\Delta\, TFP$	$\Delta\, TFP$	$\Delta\, TFP$
Food-To.	1.000	1.600	1.564	1.566
Paper	7.357	7.562	8.224	6.917
Chem	9.250	9.565	9.626	9.899
Metal	11.471	5.712	11.450	5.141
Mach.	2.961	2.712	2.924	2.993
Elect	2.615	4.851	5.717	5.228
Trans.Eq	2.374	2.225	2.782	2.788

Figure 1: Interior Optimal Techniques Choice

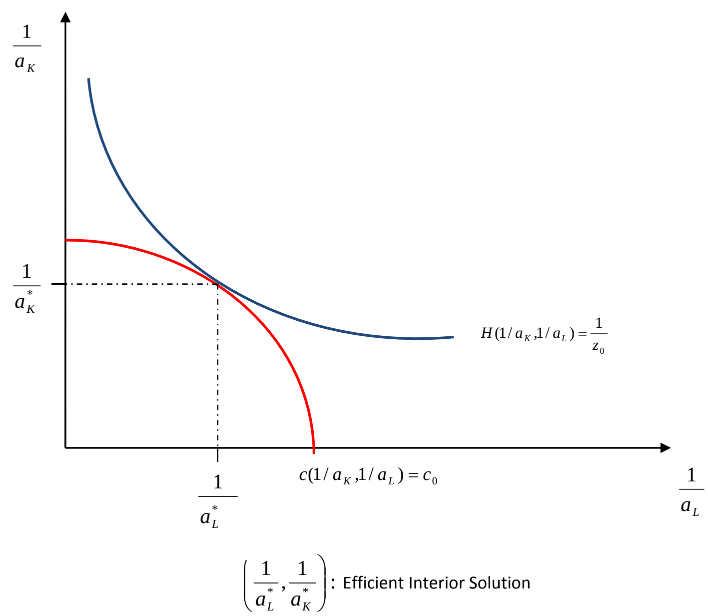


Figure 2: Techniques Choice Distortion

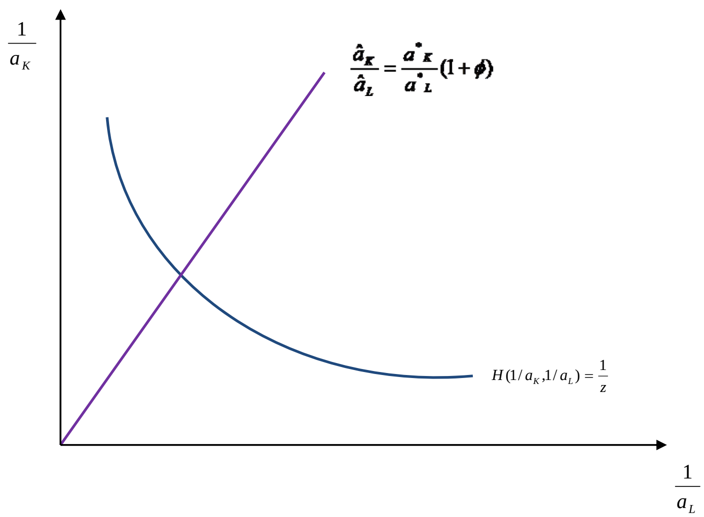
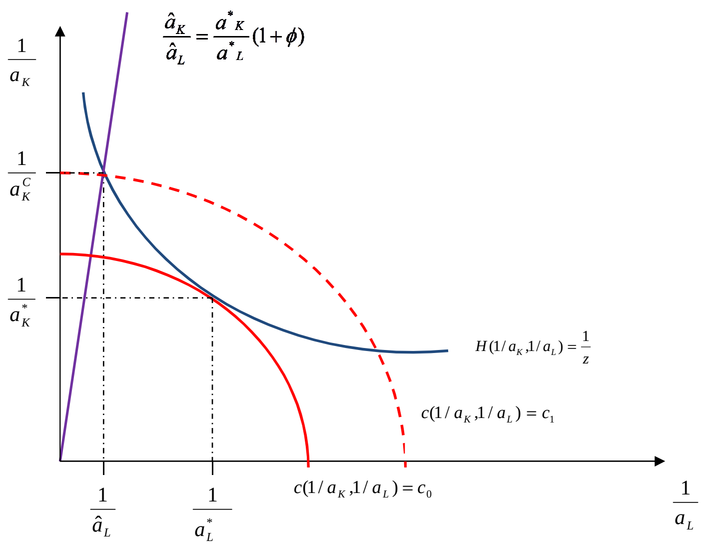


Figure 3: Technique Optimizing Problem: Efficient vs. Distorted Solution



$\left(\frac{1}{a_L^*}, \frac{1}{a_K^*}\right)$: Efficient Interior Solution

$\left(\frac{1}{\hat{a}_L}, \frac{1}{\hat{a}_K}\right)$: Distorted Interior Allocation