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Misallocation, Productivity and Development with Endogenous Production Techniques[☆]

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ABSTRACT

We study misallocation and sectoral productivity in a heterogeneous firms model with generalized production. Different from neo-classical models of production, our model endogenizes production-techniques and introduces firm-specific technique-distortions alongside factor- and scale-dependent distortions. Applying this micro-founded framework to firm-level data (US, China and India), we quantify that, for a broad range of manufacturing industry clusters, technique distortions generate more severe misallocation and sectoral TFP losses than capital and output distortions, accounting for about three quarters of the detrimental productivity effects. We thus uncover a quantitatively important channel for productivity growth and economic development resulting from within-firm organization of production.

"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

There has been a growing interest in the macro-development literature over the past decade toward uncovering the sources and the aggregate total factor productivity (TFP) consequences of misallocation across firms.[3] While making important contributions to the literature, all of these studies are rooted on a standard neo-classical production framework, where sources of inefficiency overall relate either to firms' factor input decisions (captured by capital or labor wedge) or to their scale of production (measured by output wedge). In this paper, we propose a novel approach to studying the link between misallocation and productivity. For this purpose, we construct a generalized production framework, in which firms not only decide on production factors and the scale of their output, but also on the *techniques* of production — capturing important features of within-firm organizational practices. This framework allows for the incorporation of a new source of firm-specific distortion, namely, a *technique-wedge* to the organization of optimal production, whose sectoral TFP consequences we quantify for the US, China and India.

Studying firm-level organization of production techniques can be traced back to Stigler (1939) who advocates organizational flexibility as a competitive advantage. As emphasized by Bresnahan et al. (2002), "firms do not 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).

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3 The development of the literature is due critically to increased availability of reliable micro datasets. See Restuccia and Rogerson (2013) and Hopenhayn (2014) for comprehensive surveys of the literature.

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Thus, operational efficiency requires the ability to design (and re-design) the production processes with interactive activities of various production factors, which we are after to formalize and quantify in this paper. To evaluate the role of production design as a source of inefficiency, we incorporate technique-choice imperfections into a multi-layer production framework. To do so, we adopt the generalized production framework pioneered by Houthakker (1955–1956) and revived by Jones (2005).[4] Specifically, firms in our model economy differ in technology frontiers, in factor and output distortions, and importantly also in technique-choice efficiency.

The concept of technique wedges is new, so we prefer to offer a general "accounting framework" inclusive of such new wedges regardless of the underlying model structure. To an interested reader, a microfoundation is provided in the Appendix of the paper, in which we derive firm-specific technique wedges based on limited information and limits to learning by firm managers. In this respect, we find it valuable to motivate this key feature of the model using the management science literature. In that literature it was noted for instance that "available tools for considering cost/benefit tradeoffs for investments in flexible automation often contradict the intuition of their managers" (Fine and Freund, 1990, p. 449); also, "in complex systems, firms' decision makers may not always have a precise understanding of the exact strength of the interaction between activities" (Siggelkow, 2002, p. 900).

To examine whether the proposed new source of inefficiency is quantitatively important for explaining productivity gains, we utilize firm-level balance sheet data for publicly traded firms from Compustat North-America and Global databases, in conjunction with industry-level production parameters, to separately back out manufacturing firms' capital, output and technique wedges. The use of Compustat data can be motivated based on several important points. Compustat provides detailed balance sheet information to identify each source of firm-level inefficiency and to compare the quantitative implications of our framework with the quantitative findings by the recent research on misallocation and sectoral productivity. Cross-country comparisons also become possible through the use of Compustat data. Finally, techniques-choice and organizational design are likely to be more relevant for larger scale establishments. Therefore, in order to understand the development consequences of technique-choice distortions we prefer to conduct our quantitative analysis with publicly traded (larger) firms — covered in Compustat.

Utilizing our structural framework first we measure firms' physical and revenue productivities (TFPQ and TFPR, respectively). By aggregating over a heterogeneous firms distribution, we then construct industry-level TFP estimates. 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 et al. (2021).

Our quantitative experiments yield several important insights. First, and most importantly, for both the US as well as for two large developing countries, China and India, across a variety of manufacturing industry clusters technique wedges and output distortions account for almost all the efficiency losses at the level of industry TFPs, with an impact of technique wedges in generating efficiency losses in the aggregate that is generally larger than that of output distortions. By counterfactual-based decomposition analysis, technique wedges are found to account for about three quarters of all the detrimental effects of all distortions under considerations on TFP, whereas output wedges account for about a quarter of such TFP losses. On the contrary, capital distortions are negligible for industry-level TFPs throughout — matching the findings of past research using publicly-traded firm data (from Compustat).

Second, the inefficiency impact of technique wedges get mitigated by the industry-wide flexibility of production, i.e. sectoral TFP gains from removing technique wedges are substantially smaller in industries where factors are highly substitutable. Our counterfactual-based decomposition analysis indicates that, across the board, technique wedges account for about three quarters of TFP losses from all three sources of distortions that we analyze. Third, the key quantitative findings – that technique wedges are significantly more important than capital finance distortions and largely more important than output distortions for industry TFPs – are robust to the measurement of firm-level productivity, parameter specifications, trimming outliers and the mis-measurement of capital-stock and cost of capital variables.

The technique wedge is responsible for the lion's share of misallocation, so industrial or sector-biased development policy ignoring this important wedge may lead to industrial production inefficiencies and sectoral misallocation, thus hindering economic development. Therefore, 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 wedges, which are shown to be essential for the aggregate industry productivity and argue for development policies to improve within-firm organization of production practices.

Related Literature: The paper is related to two strands of literature. One strand is on understanding the sources of misallocation and its consequences for aggregate productivity and macroeconomic development. 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. We delineate our contribution to both strands of research as follows with a discussion on positioning our paper in the literature.

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 macroeconomic output. 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 US, the TFP gap between the US 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.[5]

Similar to this strand of literature, our paper also fits in an environment of resource misallocation, where firms face factor and output distortions particularly in line with Hsieh and Klenow (2009). Yet, we go beyond by incorporating a structure to study distortions to production techniques as well and quantify the substantial impact of technique wedges on industrial TFPs. Moreover, in our framework, 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 et al. (2013) by showing that for publicly traded

[4] A primary focus of this line of research, very different from ours, 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.

[5] There is a related macro-development literature on the sources of misallocation. For example, 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. Using a measured TFP approach and secondary bond price data for publicly traded firms from the US, Gilchrist et al. (2013) provide evidence for that removing the dispersion in borrowing costs observed in the bond-price data for US manufacturing firms would improve the TFP of the manufacturing industry only by 1–2 percentage points.

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.[6,7]

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 wedges. Thus, we are able to highlight the role of inefficient technique decision making for sectoral productivity and differentiate the implications of technique wedges from those of conventional sources of factor and output distortions.

2. A generalized 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 3.

2.1. The basic environment

Let us denote capital with K and labor with L. The *combination of production techniques* is captured by a pair $\left(a_K, a_L\right)$ 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) 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.

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

$$H(a_K, a_L) = z, \tag{1}$$

$$a_K \geq \underline{a}_K > 0, \tag{2}$$

$$a_L \geq \underline{a}_L > 0, \tag{3}$$

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.[8] 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–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 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 between effective units of capital and labor inputs. The parameter λ is thus the effective capital share of production.

2.2. 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 $\left(a_K, a_L\right)$ as given; we then determine the optimal (a_K, a_L) combination.

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

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

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

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

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

[6] Along this line, Wang et al. (2018) 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.

[7] Also related to our paper, but to a lesser degree, is the framework of Caselli (1999), Acemoglu (2003). In Caselli (1999), firms decide both on production factors and techniques, whereas in Acemoglu (2003) firms undertake both labor- and capital-augmenting technological improvements.

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

2.2.1. 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.

2.2.2. 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 1 (*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 (e.g. an increase in cost of capital), it becomes 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 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.

2.3. 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 2.1 (*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.

Fig. 1 in Appendix C illustrates the interior solution as an optimal choice of production techniques. As we will delineate in Section 6, 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 industry-wide 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 case of perfect complementarity, 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, with perfect substitutes, when $\rho \to 1$ the unit 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 2.2 (*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 industry-level 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 et al. (1999), all of whom argue that overall production flexibility is an important determinant of efficiency.

3. Capital, output and technique distortionary wedges

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 jointly with factor and output distortions and technique wedges. For this purpose, we extend the specification of Section 2 to incorporate a demand structure to the benchmark model and importantly to also allow for distortions in firms' production decision margins.

Each firm takes its specific productivity term, z, and solves the following optimization program subject to capital, output and technique distortions — denoted with η_K, η_y and ϕ and to be delineated below:

$$\text{Step 1} \quad \min_{a_K,a_L} \tilde{c}(a_K,a_L;r,w,\eta_K,\eta_Y) = \left[\left(\frac{r}{a_K}\right)^{\frac{\rho}{\rho-1}}\lambda^{\frac{1}{1-\rho}} + \left(\frac{w}{a_L}\right)^{\frac{\rho}{\rho-1}}(1-\lambda)^{\frac{1}{1-\rho}}\right]^{\frac{\rho-1}{\rho}} \tag{13}$$

$$\begin{aligned} s.t.\quad & a_K^\alpha a_L^{1-\alpha} = z, \\ & a_K \geq \underline{a}_K > 0, \\ & a_L \geq \underline{a}_L > 0, \\ & \frac{a_K}{a_L} = (1+\phi)\frac{a_K^*}{a_L^*}, \\ & a_K^* = \arg\min_{a_K} \tilde{c}(a_K,a_L;r,w,\eta_K,\eta_Y), \\ & a_L^* = \arg\min_{a_L} \tilde{c}(a_K,a_L;r,w,\eta_K,\eta_Y) \end{aligned}$$

$$\text{Step 2} \quad \min_{K,L} r(1+\eta_K)K + wL \tag{14}$$

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

$$\text{Step 3} \quad \max_p (1-\eta_Y)pY^d(p) - c(r,w;\phi,\eta_K)Y^d(p) \tag{15}$$

$$s.t.\quad Y^d(p) = \left(\frac{p}{P}\right)^{-\sigma} Y_J.$$

Step 1 captures firm-level techniques choice with distortions: It simply implies that the firm's techniques-choice ratio, a_K/a_L, deviates from its (first-best) efficient benchmark by a wedge ϕ. Step 2 is the factor choice with distortions, where we introduce the firm-specific factor distortion, η_K, without loss of generality from the side of capital. Step 3 captures the choice for the output price, p, by taking the demand structure, aggregate industry price-level (P), industry-level output (Y_J) and the output distortion, η_Y. Throughout the theoretical analysis we maintain the following structural assumption.

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

3.1. Demand and output distortion

We again solve recursively by starting from the output pricing decision. 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

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

3.2. Factor choice and capital distortions

The capital cost friction can prevail from capital market imperfections as well as capital taxes, as widely discussed in the misallocation literature and 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 using firm-level data we will back out the distribution of "taxes" and "subsidies" across firms.

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.

3.3. Techniques choice with distortions

Techniques choice is subject to distortions, which prevent the firm to operate at its efficient techniques combination. The technique wedge ϕ described in step-1 of the optimization program implies that the operational capital-technique will turn out to be $\hat{a}_K = a_K^*(1+\phi)^{1-\alpha}$, with $\phi \in (-1, \bar{\phi}]$ and $\bar{\phi} > 0$, instead of a_K^*.[9] 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 Figs. 2 and 3 in Appendix C.

In our framework, the notion of imperfect technique choice is broadly defined in order to capture a spectrum of different sources of distortions to techniques decision-making at the firm-level. As we delineate in Appendix A, imperfect technique-choice can be microfounded

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

using a learning model.[10] 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 "costly learning" associated with techniques decision-making and distort technique-outcomes from an optimal benchmark as discussed by Siggelkow (2002) in a related context. Costly learning can result in deviation from the optimal a_K/a_L ratio.

The structural assumptions that govern the technique-wedge 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

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

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

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 the wedge distorts the decision on capital-techniques.

3.4. Unit cost with distortions

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

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

whose full derivation can be found in Appendix B. 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 Fig. 3 in Appendix C.

[10] In the micro-founded framework, firm managers have limited ability in production process design as argued by Bresnahan et al. (2002) or costly learning from the set of available techniques as elaborated by Fine and Freund (1990) and Siggelkow (2002).

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 distortionary wedges 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 Appendix B.

Proposition 3.1 (*Production Flexibility, Distortions and Unit Cost of Production*).

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

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

(iii) *a. if $\frac{1}{\alpha}\frac{\rho}{\rho-1} > 1$, (industry-wide) production flexibility mitigates the distortionary effects of $|\phi|$ on unit cost;*
b. if $\frac{1}{\alpha}\frac{\rho}{\rho-1} < 1$, (industry-wide) 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 distortionary wedges 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 6 will satisfy the sufficient condition (27) — promoting industry-level production flexibility as a mitigating factor of technique wedges. 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 argues that in organizational decision making process of a business, imperfect interactions between complements would be much more distortionary for the performance of the business than misperceiving the interactions between substitutes.

4. Suggestive evidence for the theoretical structure

Is there an empirically testable prediction that one can derive based on the structure of our model to confront the model 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, we observe that

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

which means that capital-labor ratio is a function of an endogenous (structural) 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

$$\frac{wL}{pY} = \frac{c(r,w;\phi,\eta_K)^{\frac{1}{1-\rho}}w^{\frac{-1}{1-\rho}}w(1-\lambda)^{\frac{1}{1-\rho}}(\hat{a}_L)^{\frac{\rho}{1-\rho}}Y}{\frac{\sigma}{\sigma-1}c(r,w;\phi,\eta_K)Y}$$

$$= \left(\frac{\sigma-1}{\sigma}\right)(1-\alpha)\cdot\underbrace{\left(\frac{1}{\Sigma(\phi)}\right)^{\frac{\rho}{\rho-1}}(1-\eta_Y)}_{=1-\tau_Y}. \tag{29}$$

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 Eqs. (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 choose production techniques – imperfectly – and in this process they face heterogeneous 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 — the database, which we will also utilize in benchmark quantitative analysis in Section 6. In our empirical analysis we focus on the manufacturing industry clusters that we list in 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 US 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 $\boldsymbol{X}_{it}$ 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 drop outliers that satisfy $\tau_Y > 1$ and $\tau_K > 50$.

We present estimation results for the regression specification (30) in Table 4 in addition to coefficient estimate from a regression where we include only industry- and time-fixed effects on the right-hand-side (without any firm-level controls). Results from both regressions show that the correlation between τ_K and τ_Y is negative and it is statistically significant at 1% level — providing an indirect suggestive empirical basis for the validity of our theoretical structure.

5. 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 an industry-level measure of total factor productivity (TFP).

5.1. Identification

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

1. Estimates for industry-level production flexibility, ρ, are based on Oberfield and Raval (2021), who measure production flexibility parameters using a Generalized CES production function. We utilize Oberfield and Raval (2021) estimates for the US benchmark and provide the distribution of the sector-level ρ parameter across the US manufacturing industries 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 2 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 NBER Productivity Database (Table 2) — for the US benchmark.
3. We apply the identification steps also utilized by Hsieh and Klenow (2009) and
   a. assume $\sigma = 3$ and $r = 0.1$,
   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 (TCK), 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 wedge:

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

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 $\frac{\text{Total Cost}}{\text{Total Revenues}}$, $\frac{\text{Total Cost}}{\text{Total Cost of Labor}}$, and $\frac{\text{Total Cost of Capital}}{\text{Capital Stock}}$ – separately and uniquely identify each of η_K, η_Y, and 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:

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

where

$$\gamma_K \equiv \left(\frac{w}{r(1+\eta_K)}\right)^{-(1-\alpha)}\left(\frac{\alpha}{1-\alpha}\right)^{(1-\alpha)\left(\frac{1-\rho}{\rho}\right)}(1+\phi)^{1-\alpha},$$

$$\gamma_L \equiv \left(\frac{w}{r(1+\eta_K)}\right)^{\alpha}\left(\frac{\alpha}{1-\alpha}\right)^{-\alpha\left(\frac{1-\rho}{\rho}\right)}(1+\phi)^{-\alpha}.$$

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

5.2. 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. The reason why we work with two alternative measures is that in one alternative technique distortions affect Total Factor Productivity of the industry through its influence on firm-level TFPQs while in the other the effects of technique distortions are channeled through firm-level TFPRs.

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 $TFPQ1$ which would yield the unit cost function characterized at (26) as

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

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 Eq. (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

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

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

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

While the second measure is elegant due to its simplicity, the first one is more profound due to its theoretical foundation. We can notice three important features of the two alternative physical productivity specifications, namely $TFPQ1$ and $TFPQ2$:

1. Factor and output distortions (η_K, η_Y) only affect $TFPR$ in both specifications.
2. technique wedges (ϕ) only affect $TFPQ1$ in the first specification.
3. technique wedges (ϕ) only affect $TFPR2$ in the second specification.
4. Therefore, while TFPQ1 measure accounts all gains from mitigating technique wedges to the physical productivity, the TFPQ2 measure accounts all gains from eliminating technique wedges to the revenue productivity.

As we will show in the next section these two alternative TFPQ measures (and implied TFPRs) 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 any special-case measurements of firm-level productivity.

Table 1
Classification of manufacturing industries.

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

5.3. Aggregation: Industry-level total factor productivity

In order to measure industry-level TFP let us 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

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

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

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

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.

6. 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 uncover the effects of capital, output and technique distortions on industry-level TFP.

6.1. Firm-level data

To conduct our quantitative analysis, we use firm-level balance sheet data from Compustat North America and Compustat Global. The choice of organizational production techniques is likely to be a relevant concept for larger scale establishments, which are covered by the publicly listed firm databases in Compustat. Moreover, Compustat also provides the possibility for meaningful cross-country comparisons.

Table 2
Structural parameters.

Industry cluster	α	ρ
Food-Tobacco	0.22	−0.15
Paper-Printing	0.25	−1.5
Chemical-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 (2021), 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
Chemical-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). # Obs is the short-cut for "total number of observations".

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
Chemical-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
Regressions with τ_Y and τ_K: Dependent variable τ_Y.

τ_K	−2.99*** (1.08)	−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	3,321	2,334
R-sq	0.0165	0.0246

We use several waves of cross-sectional manufacturing sector data between the years of 1995 and 2014. 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".

Table 5
Distributional properties of firm-variables.

Variable name	Mean	Std. Dev.	Min	Max	# Obs.
ln(Labor)	6.47	2.41	0	13.52	50 805
ln(Capital)	17.29	3.01	6.90	26.54	56 077
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	55 955
ln(Total Revenue)	18.62	2.96	6.90	26.88	54 476

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.

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 (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 (data-names *ppegt* and *ppent* respectively). 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 $I_{it} - \delta K_{it} = ppent_{it+1} - ppent_{it}$.
3. **Total labor cost (wL)** is captured by the *total staff expense* data item in Compustat (data name *xlr*).
4. **Total capital cost ($r(1+\eta_K)K$)** is generated by summing up the *capital expenditures* data item in Compustat for the current period with $r(1-\delta)K$ from the previous period, where $r = 0.1$ and $\delta = 0.05$ as in Hsieh and Klenow (2009). (data name for capital expenditures is *capx*).
5. **Total revenue (TR)** is captured by the total revenue data item in Compustat (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 for the US benchmark 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 (2021). To the end of the latter, the authors utilize US 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 as we document in Table 2.

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 6.4.2 we will check the sensitivity of our results with respect to variations in r and σ.

6.2. US benchmark

Based on the data items listed above we proxy firm level measures of TFPQ and TFPR (using the two alternative methods, $(TFPQi, TFPRi)$, $i = 1, 2$) and quantify sectoral benchmark TFPs for the US economy by using the aggregation rule (43) for each industry-cluster over the time-period 1995–2015 — as we described in Section 5. As an important

Table 6
Industry-level relative TFPs.

Industry	1995		2005		2014	
	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 Eq.(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 Eq. (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 Eq. (39).

Table 7c
Distribution of lnTFPR2.

Industry	1995			2005			2014		
	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 Eq. (41).

quantitative feature of the benchmark framework, we choose the limit techniques $\underline{a}_K$ and $\underline{a}_L$ such that the distribution of technique wedges 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 Appendix C (C.6a–C.6d) we provide results for additional years between 1996–2012. Notably, if we trim outliers of computed wedges by 15%, those large estimates would no longer exist.

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 measures TFPQ1 and TFPQ2. Particularly, in years 2005 and 2014 the TFP-ranking of industries coincide completely when TFPQ1 and TFPQ2 physical-productivity measures are applied.[11]

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, since $TFPQ2$ is equivalent to $\hat{z}$.

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 wedges, ϕ's, are different than zero-optimum throughout the years and across the industry clusters — with significantly large dispersions, which promotes technique wedges 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.

6.3. Counterfactual experiments with US benchmark

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) and influence the aggregate development if we were to reduce the distortions originating from capital, output and technique decisions of the production process.

Before we proceed with the presentation of results we would like to note that for the case of TFPQ2 measure, we will only provide quantitative results with respect to technique wedges, 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 Appendix C Tables C.6a–C.6d.

6.3.1. 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 distortionary wedges, 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

[11] 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.

Table 8a
Distribution of η_K.

Industry	1995			2005			2014		
	Mean	S. Dev	# Obs	Mean	S. Dev	# Obs	Mean	S. Dev	# 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 Eq. (34).

Table 8b
Distribution of η_Y.

Industry	1995			2005			2014		
	Mean	S. Dev	# Obs	Mean	S. Dev	# Obs	Mean	S. Dev	# 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 Eq. (31).

Table 8c
Distribution of ϕ.

Industry	1995			2005			2014		
	Mean	S. Dev	# Obs	Mean	S. Dev	# Obs	Mean	S. Dev	# 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 wedge ϕ is backed out using Eq. (33).

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

Industry	1995			2005			2014		
	Mean	S. Dev	# Obs	Mean	S. Dev	# Obs	Mean	S. Dev	# 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 Eq. (35), where $TFPQ2 \equiv \hat{z}$.

of the quantitative analysis $\Delta TFP > 1$ indicates an expansion in the industry-TFP (aggregate development) in response to the removal of 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.

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

Industry	1995	2005	2014
	ΔTFP	ΔTFP	ΔTFP
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 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 ΔTFP 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.

The negligible TFP consequences of capital distortions that we capture in our framework align with the findings of Gilchrist et al. (2013). Using a measured TFP approach and secondary bond price data also for publicly traded firms from Compustat North America, Gilchrist et al. (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 generated 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 wedges are quantitatively very significant in generating efficiency losses and reducing industry TFPs, where in many industry cases (such as 5 out of 7 industries for the year of 2014) the TFP effects of technique wedges are the most consequential among three sources of distortions*. In all three years, for which we provide quantitative results, reducing the technique wedges to zero for all firms results in TFP gains that for most industries exceed 100% of the benchmark industry TFP.

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

Industry	1995	2005	2014
	ΔTFP	ΔTFP	ΔTFP
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.

Industry	1995	2005	2014
	ΔTFP	ΔTFP	ΔTFP
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 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 9d
Setting $\phi = 0$ with TFPQ2.

Industry	**1995**	**2005**	**2014**
	ΔTFP	ΔTFP	ΔTFP
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			
Industry	**1995**	**2005**	**2014**
	ΔTFP	ΔTFP	ΔTFP
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

As we illustrate in Appendix C Tables C.6a–C.6d, strong and persistent quantitative effects of technique wedges 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.

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

For $\rho = -0.15$ in all industries			
	1995	2005	2014
Industry	ΔTFP	ΔTFP	ΔTFP
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.

6.3.2. 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 wedge 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 wedges 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 wedges 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 wedges 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 wedges. Thus, our main quantitative findings are not sensitive to the measurement of firm-level productivities.

6.3.3. Flexibility and TFP gains

The results presented in Tables 9c and 9d reveal the substantial implications of technique wedges for industry TFPs. An important feature of our theoretical structure is the mitigating effect of industrial production flexibility, ρ, on counterproductive consequences of technique wedges. The generalized production framework allows us to investigate this property associated with industry-level factor flexibility. 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 wedges?

As one can observe in the expressions for TFPQ1 (at (38)) and TFPR2 (at (41)), flexibility of production mitigates technique wedges 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) at Proposition 4.1 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) of Proposition 4.1 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 wedges. Hence, the TFP gains from removing technique wedges are expected to be the highest in industries in which the efficient units of capital and labor are strong complements.

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

For $\rho = -0.15$ in all industries	1995		2005		2014	
Industry	ΔTFP	Contrib. of ρ to ΔTFP	ΔTFP	Contrib. of ρ to ΔTFP	ΔTFP	Contrib. of ρ to ΔTFP
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	1995		2005		2014	
Industry	ΔTFP	Contrib. of ρ to ΔTFP	ΔTFP	Contrib. of ρ to ΔTFP	ΔTFP	Contrib. of ρ to ΔTFP
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 ΔTFP" 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
Decomposition of Detrimental TFP Effects (TFPQ1).

	Capital wedge	Output wedge	Technique wedge	Total
Average over industries				
1995	0.4%	7.5%	92.0%	100%
2005	−0.2%	17.0%	83.1%	100%
2014	0.1%	51.6%	48.3%	100%
Average over time				
Food-To.	−0.3%	58.6%	41.7%	100%
Paper	0.0%	2.5%	97.5%	100%
Chem	0.0%	25.3%	74.7%	100%
Metal	0.0%	1.1%	98.9%	100%
Mach.	0.1%	36.5%	63.4%	100%
Elect	0.8%	39.2%	60.0%	100%
Trans.Eq	0.7%	22.2%	77.1%	100%
Overall Avg.	0.1%	23.6%	76.3%	100.0%

Table 10b
Decomposition of Detrimental TFP Effects (TFPQ2).

	Capital wedge	Output wedge	Technique wedge	Total
Average over industries				
1995	0.5%	9.6%	90.0%	100.0%
2005	−0.3%	19.1%	81.1%	100.0%
2014	0.1%	52.6%	47.4%	100.0%
Average over time				
Food-To.	−0.9%	78.4%	22.5%	100.0%
Paper	0.0%	4.2%	95.8%	100.0%
Chem	0.0%	26.6%	73.4%	100.0%
Metal	−0.2%	2.4%	97.8%	100.0%
Mach.	0.1%	38.1%	61.8%	100.0%
Elect	0.8%	39.7%	59.5%	100.0%
Trans.Eq	0.6%	25.8%	73.5%	100.0%
Overall Avg.	0.1%	25.8%	74.2%	100.0%

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 wedges. 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 wedges. Machinery, Electrical Equipments and Transportation Equipments industries have intermediate levels of flexibility and these industries have mediocre potential of TFP-growth from correcting technique wedges.

In order to deepen our understanding on the interaction of industry-flexibility with technique wedges 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 wedges. 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 wedges. 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 wedges 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 wedges vanishes. As we also report in Tables 9g and 9h, 40%–80% of TFP gains from reducing technique wedges 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 channel the TFP consequences of technique wedges.

6.3.4. Decomposition of TFP effects

In Tables 10a and 10b we provide a decomposition analysis for the detrimental TFP effects of distortionary wedges based on what we presented in Tables 9a-d. In both tables we present results over time and across industry classifications. The quantitative results from this analysis allow us to conclude that technique wedge is by far the most important source of inefficiency across all industries and over time, accounting for about three quarters of all detrimental distortionary effects on TFP and almost all of such TFP losses in Paper and Metal industries. As also highlighted before, capital wedge is inconsequential throughout. Output wedge accounts for about a quarter of the detrimental TFP effects; it becomes more important over time and is particularly important in Food & Tobacco industry. Finally, our findings are robust regardless of the application of TFPQ1 or TFPQ2 as the physical productivity measure.

6.4. Cross-country comparisons: India and China

Next we would like to tackle whether persistent and quantitatively significant efficiency losses associated with technique wedges 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 India and China. We choose the Compustat Global-data for the cross-country analysis in order to work with datasets that are by nature comparable to the US Benchmark: working with Compustat Global allows to compare publicly traded firms in the US 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 US) 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 wedges could also be important for the efficiency losses of publicly traded firms in developing countries.

Tables 11a and 11b present descriptive statistics of firm-level variables for the country-cases of China and India 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 US Benchmark), the distributional properties here 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 US parameters $(r, \sigma; \alpha, \rho)$, 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 12a–12b (13a–13b) 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, since for the case of China in 2005 manufacturing data for Food-Tobacco and Paper industry clusters are not available, we do not analyze those two industries in 2005 for China.

Table 11a
India: Distributional properties of firm-variables.

Variable name	Mean	Std. Dev.	Min	Max	# Obs.
ln(Labor)	6.63	6.63	0	11.79	16 977
ln(Capital)	19.92	2.00	8.69	28.42	67 828
ln(Total Labor Cost)	17.44	2.45	6.90	26.27	68 561
ln(Total Capital Cost)	19.75	2.01	7.60	28.47	63 520
ln(Total Revenue)	20.35	2.25	6.90	29.21	69 837

Table 11b
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	59 039
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	54 759
ln(Total Revenue)	20.49	1.27	6.90	28.45	64 684

Table Notes. Firm-level averages in Tables 10a–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 12a
India: Setting $\eta_K = 0$ and $\eta_Y = 0$.

	$\eta_K = 0$		$\eta_Y = 0$	
	2005	2014	2005	2014
Industry	ΔTFP	ΔTFP	ΔTFP	ΔTFP
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

The results indicate 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 US manufacturing industries. 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 India and China 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 US benchmark.

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

6.5. Robustness

In this section we test the sensitivity of our main findings from the US benchmark analysis with respect to the specification of production framework, the benchmark values of macro parameters, outliers, the potential mismeasurement of firm-level variables, and finally the relative benchmark of counterfactual policy experiments. All tables associated with the robustness analysis are included in Appendix C.

Table 12b
India: Setting $\phi = 0$.

	$\phi = 0$ with $TFPQ1$		$\phi = 0$ with $TFPQ2$	
	2005	2014	2005	2014
Industry	ΔTFP	ΔTFP	ΔTFP	ΔTFP
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 13a
China: Setting $\eta_K = 0$ and $\eta_Y = 0$.

	$\eta_K = 0$		$\eta_Y = 0$	
	2005	2014	2005	2014
Industry	ΔTFP	ΔTFP	ΔTFP	ΔTFP
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 13b
China: Setting $\phi = 0$.

	$\phi = 0$ with $TFPQ1$		$\phi = 0$ with $TFPQ2$	
	2005	2014	2005	2014
Industry	ΔTFP	ΔTFP	ΔTFP	ΔTFP
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

First, we offer a comparison with the special case of neoclassical production function,

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

where $TFPQ$ is given by $TFPQ = \hat{z}$ and $a_K = a_L = \hat{z}$ is exogenously set for all firms. Thus, there is no flexible techniques decision-making at the firm-level. Using this alternative specification 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 are reported in Tables C.1a and C.1b in Appendix C (for the years of 1995, 2005 and 2014). We find that capital distortions are still negligible while output distortions are substantial in determining the TFP efficiency losses. This important result shows that the quantitative TFP effects of capital and output distortions that we captured previously are not sensitive to our "generalized production framework" specification.

Second, we turn to checking whether our results are sensitive to typical parametrization as in Hsieh and Klenow (2009): the average cost of capital r and the elasticity of substitution σ across Dixit–Stiglitz varieties within an industry. In Appendix Tables C2a–b and C3a–b in, we check the sensitivity of our TFP counterfactual results changing the value of σ from 3 to 2 and 4 and r from 0.1 to 0.07 and 0.13 (for the year of 2014 for the sake of brevity). We find essentially no change from our previous primary quantitative findings, in relative roles played by capital and output distortions and technique wedges in determining industry TFPs and in the role of ρ for mitigating the distortionary effects of technique imperfections.

Third, we perform a robustness test by eliminating outlier-firms from the analysis based on the level of revenue productivities, TFPR1 and TFPR2 (for the year of 2014). It is noted that when backing out the technique wedges 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 reported in Appendix Tables C.4a (and C.4b) 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), which reduces the sample sizes by 10%–20%. As can be seen in Tables C4a–b, the primary quantitative findings fully remain.

Fourth, we turn to the more subtle issue of mismeasurement. Among the five firm-level variables used in our quantitative exercises (namely, number of employees, total cost of labor, capital stock, total cost of capital, and revenues) capital stock, total cost of capital, and revenues might be prone to some mismeasurement problems. To address these concerns, we provide the following theoretical and quantitative exercises.

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 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:

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

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

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

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 wedge 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 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 focus on two aggregate cases. In a set of alternative TFP counterfactual exercises we assume that the total cost of capital to be 15% larger (smaller) than the benchmark measurement and report the results in Table C.5a (Table C.5b), again for the year of 2014. The results reveal that our previous findings are robust to a uniform mismeasurement of total cost of capital across firms. Specifically, assuming that for all firms the total cost of capital is systematically larger (or smaller) than what we captured in the benchmark 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.

Next, we study the robustness of our results with respect to the inclusion of intermediate inputs. For this purpose we first consider a structural approach by assuming that the total output of a firm is given by $\mathcal{Y} = Y^{\upsilon} I^{1-\upsilon}$, where Y captures firm's output net of intermediate inputs, I represents the intermediate inputs and υ is the share of intermediate inputs in production. Firm's output net of intermediates is produced by combining capital (K) and labor (L) as specified previously. Suppose that υ is determined at the level of the industry and also that the unit cost of intermediate inputs for all firms equal to q within an industry. This framework allows us to obtain the structural revenues net of intermediate inputs as $\frac{p\mathcal{Y}}{\left(\frac{1-\upsilon}{q}\right)^{\frac{1-\upsilon}{\upsilon}}}$. Since $\left(\frac{1-\upsilon}{q}\right)^{\frac{1-\upsilon}{\upsilon}}$ is an industry-wide multiplier, it does not impact the quantitative TFP implications of distortionary wedges. This means as long as firms' unit costs of intermediate inputs do not exhibit heterogeneity, firms' intermediate input demand would not alter the conclusions we obtained in our benchmark analysis with regard to TFP effects of technique, capital, and output distortions.

However, unit cost of intermediate inputs may show heterogeneity across firms. In Tables C.7a–C.7d, we take this potential heterogeneity into account. Following, De Loecker et al. (2020), we utilize the *cost of goods sold* data item of Compustat – net of the total cost labor – as a measure for the cost of (variable) intermediate inputs at the firm level. We compute the net revenues for each firm by subtracting the intermediate inputs cost from revenues and performing the quantitative analyses using this net revenues measure.[12]

As the results presented in Tables C.7a–C.7d reveal, our main findings largely remain the same after incorporating firm-level intermediate inputs in our analysis, with large TFP gains from removing technique distortions and negligible TFP impact of capital distortions across the spectrum of manufacturing industries.

Fifth and lastly, we explore the implications of altering the nature of our counterfactual experiments. Our main quantitative analyses concentrate on reducing the distortions to a level of zero and then computing TFP gains (i.e., η_K, η_Y, and ϕ were set equal to zero in the counterfactual analyses). As a final robustness check, we set capital, output and technique distortions equal to their mean values – denoted with $\bar{\eta}_K$, $\bar{\eta}_Y$, and $\bar{\phi}$ respectively – in a particular industry & year combination and quantify the counterfactual implications of eliminating distortions. For the case of η_K counterfactual, this exercise is quite useful, because setting $\eta_K = \bar{\eta}_K$ for all firms helps to measure TFP effects of eliminating capital distortions in a manner that keeps the average capital input constant within an industry. We report the results from these alternative quantitative analyses in Tables C.8a–C.8d.

Altering the counterfactual target from $\eta_K = 0$ to $\eta_K = \bar{\eta}_K$ for the case of capital distortions causes a negligibly small change with respect to the TFP effects of capital distortions compared to what we captured in the main quantitative analysis: we continue to observe a minimal impact for the capital distortions on TFP also with $\eta_K = \bar{\eta}_K$. For the case of output distortions, changing the counterfactual target to $\eta_Y = \bar{\eta}_Y$ causes no change for the counterfactual TFP impact of output distortions, because as it can be observed from the TFP (Eq. (43)) and TFPR (Eqs. (39) and (44)) expressions, including a factor of $\overline{(1-\eta_Y)}$ in the counterfactual TFPR for all firms is equivalent to not including this factor at the firm-level TFPR (as we did in $\eta_Y = 0$ counterfactual) while taking into account that $\overline{(1-\eta_Y)}$ then gets to enter in the comparison of industry-level $\overline{TFPR}$'s between the benchmark and counterfactual cases. A similar conclusion is obtained for the counterfactuals of $\phi = \bar{\phi}$ (with TFPQ1 and TFPQ2), where changing the target of $\phi = 0$ in the counterfactuals to $\phi = \bar{\phi}$ switches the impact of eliminating technique wedges on TFP between what we had reported in the main quantitative analyses for the counterfactuals with TFPQ1 and TFPQ2.

[12] There is not a strong correlation between the level of revenues and the share of intermediate inputs in Compustat data, where the correlation coefficient for the relationship between revenues and intermediate input share (i.e., intermediate-inputs-cost/total revenues) is −0.003.

7. Concluding remarks

We have developed a generalized production framework, where firms decide on their output scale, production factors 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, technique wedges and output distortions, we have developed an aggregated measure of industry TFP. We have then examined the consequences of capital, output and technique distortionary wedges 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 and technique wedges raise the unit cost of production, substitutability between technique-augmented factors reduces the efficiency losses borne by technique wedges: The detrimental effects of capital financing distortions are independent of the extent of industry-level production flexibility, but the detrimental effects of technique imperfections are amplified by industry production inflexibility.

We have undertaken a number of quantitative exercises by calibrating the model to fit the observations from firm-level data in manufacturing industries. Our quantitative results can be summarized as the following: (i) for all manufacturing industry-clusters – throughout the years of the analysis – technique wedges and output distortions account for most of the efficiency losses at the level of industry TFPs; (ii) the impact of technique wedges in generating efficiency losses in the aggregate is generally larger than that of the output distortions for many industry-clusters and over time; (iii) capital distortions have a largely negligible impact on industry-level TFPs; (iv) the overall quantitative findings are comparable across US, China and India; (iv) the inefficiency impact of technique wedges get mitigated by the industry-wide flexibility of production, implying that TFP gains from removing technique wedges are larger in industries where efficient units of capital and labor exhibit strong complementarity.

An important policy implication arising from our analysis is that to achieve greater production efficiency and macroeconomic development, mitigating technique imperfections should be granted with high priority. Such policy arrangement may include, but not limited to, tax incentives for flexible manufacturing systems.

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

CRediT authorship contribution statement

Burak R. Uras: Conceptualization, Data curation, Formal analysis, Funding acquisition, Investigation, Methodology, Project administration, Resources, Software, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing. **Ping Wang:** Conceptualization, Data curation, Formal analysis, Funding acquisition, Investigation, Methodology, Project administration, Resources, Software, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing.

Declaration of competing interest

With this document we declare that as the authors of this manuscript we have no conflict of interest resulting from the research presented in our manuscript.

Data availability

The authors do not have permission to share data.

Appendix A

To rationalize technique wedge ϕ as an outcome of endogenous decision making, consider a learning cost $\Xi(e)$ where $e \in [0,1]$ is learning intensity. Notably,

$$\hat{a}_K^{\alpha}\hat{a}_L^{1-\alpha} = (1+\phi)^{\alpha(1-\alpha)}(1+\phi)^{-\alpha(1-\alpha)}\left(a_K^*\right)^{\alpha}\left(a_L^*\right)^{1-\alpha} = \left(a_K^*\right)^{\alpha}\left(a_L^*\right)^{1-\alpha} = z$$

that is, by construction, even with imperfect technique choice, the techniques constraint $H(a_K,a_L) = a_K^{\alpha}a_L^{1-\alpha} = z$ is unchanged. This means one cannot rationalize the endogenous technique choice via endogenous choice of menu. Rather one should rationalize it based on the technique gap between $(\hat{a}_K,\hat{a}_L)$ and $\left(a_K^*,a_L^*\right)$.

To begin, we measure the benefit from reducing the gap. For simplicity, let us measure the gap in a_K/a_L-ratio in a quadratic form (nonsmooth in the absolute-value form):

$$gap = \left(\frac{\hat{a}_K/\hat{a}_L - 1}{a_K^*/a_L^*}\right)^2 = \phi^2$$

Let the benefit be logistic given by

$$B(gap) = \frac{2}{1+\exp(gap)},$$

which is well-defined with $B(0) = 1$, $B(\infty) = 0$, $B' < 0$ and $B'' < 0$. Next, let learning technology be Ricardian:

$$gap(e) = \vartheta\cdot(1-e)$$

with $gap(0) = \vartheta > 0$, $gap(1) = 0$ and $gap' < 0$. Finally, let learning cost be quadratic:

$$\Xi(e) = \xi e^2,$$

where ξ is subject to a firm-specific distortionary wedge as a result of production design frictions. Then the optimization problem of Stage 2 in our model can be specified as:

$$\max_e B(gap(e)) - \Xi(e)$$

or, by substituting in functional forms:

$$\max_e 2\left[1+\exp(\vartheta\cdot(1-e))\right]^{-1} - \xi e^2.$$

The first-order condition is

$$D(e) \equiv \vartheta\left[1+\exp(\vartheta\cdot(1-e))\right]^{-2}\exp(\vartheta\cdot(1-e)) = \xi e,$$

where it is easily shown that $D' = -\vartheta\left[1+\exp(\vartheta\cdot(1-e))\right]^{-3}\exp(\vartheta\cdot(1-e)) < 0$, $= \vartheta\left[1+\exp(\vartheta)\right]^{-2}\exp(\vartheta) > 0 = \Xi'(0)$ and $D(1) = \vartheta/4$. Thus, we have an interior solution of effort intensity if

$$D(1) = \vartheta/4 \le \xi = \Xi'(1).$$

Let $e^*(\xi)$ solve $D(e^*) = \xi e^*$. It is clear that $e^*(\xi)$ is decreasing in ξ and at its minimum support $e^*(\vartheta/4) = 1$. Denote the mean of ξ as $\bar{\xi}$ and the corresponding effort intensity as $\bar{e}^*$. We can then back out

$$\phi = \pm\sqrt{gap(e^*)} = \pm\sqrt{\vartheta\cdot[1-e^*(\xi)]},$$

with $\phi \gtrless 0$ iff $\xi \gtrless \bar{\xi}$. The above expression therefore links production design friction ξ to technique wedge ϕ with larger production design frictions leading to greater technique wedge.

Appendix B

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

$$K\ :\ r = \mu_1\lambda a_K^{\rho}K^{\rho-1}[(a_K K)^{\rho} + (a_L L)^{\rho}]^{\frac{1-\rho}{\rho}}$$

$$\Rightarrow\quad K = \mu_1^{\frac{1}{1-\rho}} r^{\frac{-1}{1-\rho}} \lambda^{\frac{1}{1-\rho}} a_K^{\frac{\rho}{1-\rho}} Y; \tag{49}$$

$$L\ :\ w = \mu_1(1-\lambda)a_L^{\rho}L^{\rho-1}[(a_K K)^{\rho} + (a_L L)^{\rho}]^{\frac{1-\rho}{\rho}}$$

$$\Rightarrow\quad L = \mu_1^{\frac{1}{1-\rho}} w^{\frac{-1}{1-\rho}} (1-\lambda)^{\frac{1}{1-\rho}} a_L^{\frac{\rho}{1-\rho}} Y. \tag{50}$$

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

$$a_K\ :\ r^{\frac{\rho}{\rho-1}}\lambda^{\frac{1}{1-\rho}}a_K^{-\frac{\rho}{\rho-1}-1}\left[\left(\frac{r}{a_K}\right)^{\frac{\rho}{\rho-1}}\lambda^{\frac{1}{1-\rho}} + \left(\frac{w}{a_L}\right)^{\frac{\rho}{\rho-1}}(1-\lambda)^{\frac{1}{1-\rho}}\right]^{\frac{\rho-1}{\rho}-1}$$

$$= \mu_2\alpha a_K^{\alpha-1}a_L^{1-\alpha}, \tag{51}$$

$$a_L\ :\ w^{\frac{\rho}{\rho-1}}(1\text{-}\lambda)^{\frac{1}{1-\rho}}a_L^{-\frac{\rho}{\rho-1}-1}\left[\left(\frac{r}{a_K}\right)^{\frac{\rho}{\rho-1}}\lambda^{\frac{1}{1-\rho}} + \left(\frac{w}{a_L}\right)^{\frac{\rho}{\rho-1}}(1\text{-}\lambda)^{\frac{1}{1-\rho}}\right]^{\frac{\rho-1}{\rho}-1}$$

$$= \mu_2(1\text{-}\alpha)a_K^{\alpha}a_L^{-\alpha}. \tag{52}$$

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 2.1

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 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

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

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

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

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

Using (54), we can see that

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

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

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 2.2

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, $\lambda^{\alpha}(1-\lambda)^{1-\alpha} \le \alpha^{\alpha}(1-\alpha)^{1-\alpha}$ 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.

Stage-4. $\max_{p} \ (1-\eta_Y)pY^d(p) - c(\phi, \eta)Y^d(p) = \left[(1-\eta_Y)p - c(\phi, \eta)\right] Y^d(p)$

$$s.t. \ \ Y^d(p) = \left(\frac{p}{P}\right)^{-\sigma} Y_J.$$

First-order conditions are

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

which provides the pricing function.

Stage-3. $\min_{K,L} \ r(1+\eta_K)K + wL$

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

First-order conditions are

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

$$w = MPL = \mu\frac{(1-\lambda)(a_L L)^{\rho}}{\lambda(a_K K)^{\rho} + (1-\lambda)(a_L L)^{\rho}}\frac{Y}{L}$$

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

$$(1+\eta_K)rK + wL = \mu\frac{\lambda\left(a_K K\right)^{\rho} + (1-\lambda)(a_L L)^{\rho}}{\lambda(a_K K)^{\rho} + (1-\lambda)(a_L L)^{\rho}}Y, \text{ or, } c = \mu$$

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

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

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

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

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

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 technique wedges, 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.

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

or,

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

Proof of Proposition 3.1

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

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

And, also observe that:

$$\frac{\partial^2 c}{\partial\Phi\partial\rho} \propto \frac{\partial}{\partial\rho}\left[1-\alpha\left(1-\Phi^{\frac{\rho}{1-\rho}}\right)\right]^{\frac{-1}{\rho}}\left(1-\Phi^{\frac{\rho}{1-\rho}}\right)$$
$$= \left[1-\alpha\left(1-\Phi^{\frac{\rho}{1-\rho}}\right)\right]^{\frac{-1}{\rho}}\left(1-\Phi^{\frac{\rho}{1-\rho}}\right)\frac{1}{\rho^2}\ln\left(1-\alpha\left(1-\Phi^{\frac{\rho}{1-\rho}}\right)\right)$$
$$+\left(\frac{-1}{\rho}\right)\left[1-\alpha\left(1-\Phi^{\frac{\rho}{1-\rho}}\right)\right]^{\frac{-1}{\rho}-1}\alpha\frac{1}{(1-\rho)^2}\ln(\Phi)\left(1-\Phi^{\frac{\rho}{1-\rho}}\right)$$
$$-\left[1-\alpha\left(1-\Phi^{\frac{\rho}{1-\rho}}\right)\right]^{\frac{-1}{\rho}}\frac{1}{(1-\rho)^2}\ln(\Phi)$$
$$\propto \left(1-\Phi^{\frac{\rho}{1-\rho}}\right)\frac{1}{\rho^2}\ln\left(1-\alpha\left(1-\Phi^{\frac{\rho}{1-\rho}}\right)\right)$$
$$-\left\{1-\left(\frac{-1}{\rho}\right)\left[1-\alpha\left(1-\Phi^{\frac{\rho}{1-\rho}}\right)\right]^{-1}\alpha\left(1-\Phi^{\frac{\rho}{1-\rho}}\right)\right\}\frac{1}{(1-\rho)^2}\ln(\Phi)$$

< 0 for the case of $\Phi > 1$ and $\rho < 0$ if

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

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.

Appendix C

In this Appendix, we provide supplementary tables to the quantitative analysis (for Section 6) and supplementary figures (for Sections 2 and 3).

Table C.1a
Setting $\eta_K = 0$ with Neo-classical production.

Industry	1995	2005	2014
	ΔTFP	ΔTFP	ΔTFP
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 C.1b
Setting $\eta_Y = 0$ with Neo-classical production.

Industry	1995	2005	2014
	ΔTFP	ΔTFP	ΔTFP
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 C1a–b present counterfactual experiments, where – instead of the staged-decision making production with techniques choice – a Neo-classical production framework is used with $\hat{z} \equiv TFPQ$.

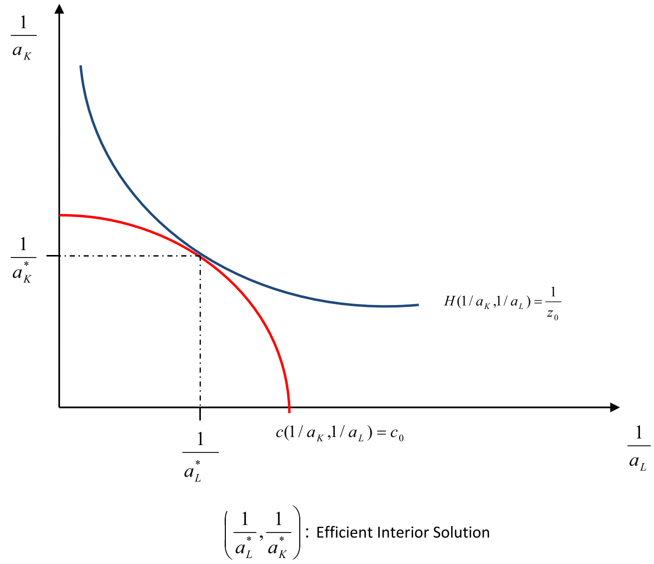

Fig. 1. Interior optimal techniques choice.

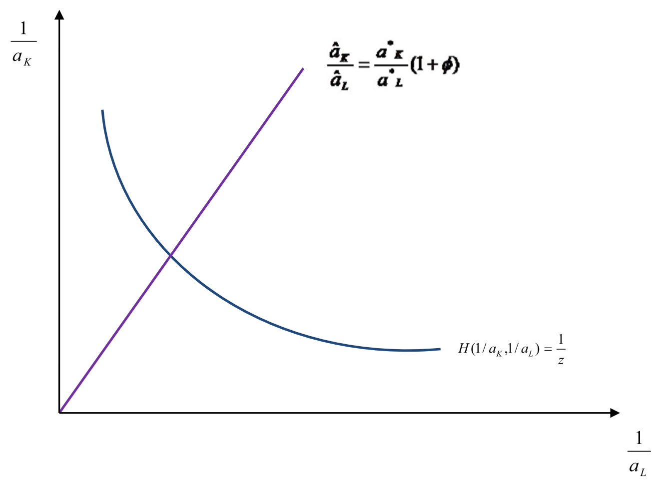

Fig. 2. Techniques choice distortion.

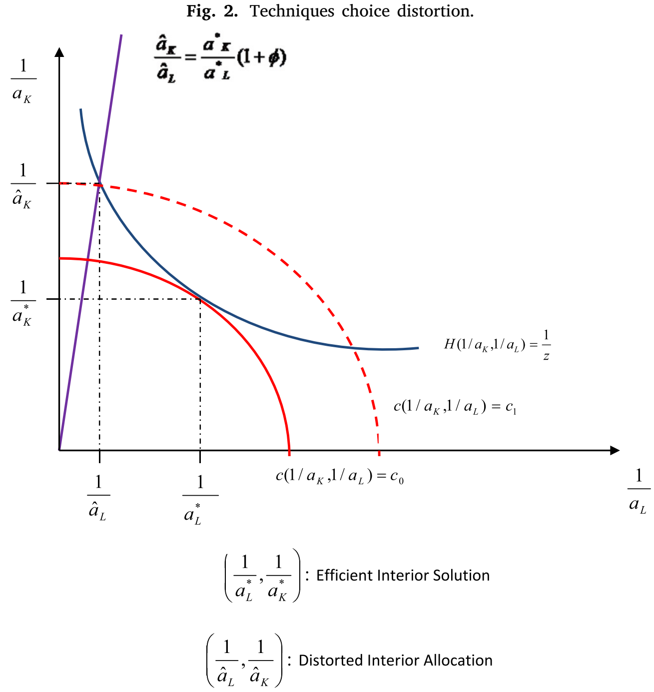

Fig. 3. Technique optimizing problem: Efficient vs. Distorted solution.

Table C.2a
Misallocation counterfactuals with $\sigma = 2$ (Year 2014).

Industry	ΔTFP from $\eta_K = 0$	ΔTFP from $\eta_Y = 0$	ΔTFP from $\phi = 0$ (TFPQ1)	ΔTFP 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 C.2b
Misallocation counterfactuals with $\sigma = 4$ (Year 2014).

Industry	ΔTFP from $\eta_K = 0$	ΔTFP from $\eta_Y = 0$	ΔTFP from $\phi = 0$ (TFPQ1)	ΔTFP 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 C.3a
Misallocation counterfactuals with $r = 0.07$ (Year 2014).

Industry	ΔTFP from $\eta_K = 0$	ΔTFP from $\eta_Y = 0$	ΔTFP from $\phi = 0$ (TFPQ1)	ΔTFP 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 C.3b
Misallocation counterfactuals with $r = 0.13$ (Year 2014).

Industry	ΔTFP from $\eta_K = 0$	ΔTFP from $\eta_Y = 0$	ΔTFP from $\phi = 0$ (TFPQ1)	ΔTFP 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 C.4a
Misallocation counterfactuals with constrained TFPR1-dispersion (Year 2014).

Industry	ΔTFP from $\eta_K = 0$	ΔTFP from $\eta_Y = 0$	ΔTFP from $\phi = 0$ (TFPQ1)	ΔTFP 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 C.4b
Misallocation counterfactuals with constrained TFPR2-dispersion (Year 2014).

Industry	ΔTFP from $\eta_K = 0$	ΔTFP from $\eta_Y = 0$	ΔTFP from $\phi = 0$ (TFPQ1)	ΔTFP 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 C.4a (C.4b) 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 C.5a
Misallocation counterfactuals with 15% larger TC of Capital (Year 2014).

Industry	ΔTFP from $\eta_K = 0$	ΔTFP from $\eta_Y = 0$	ΔTFP from $\phi = 0$ (TFPQ1)	ΔTFP 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 C.5b
Misallocation counterfactuals with 15% smaller TC of Capital (Year 2014).

Industry	ΔTFP from $\eta_K = 0$	ΔTFP from $\eta_Y = 0$	ΔTFP from $\phi = 0$ (TFPQ1)	ΔTFP 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 C.5a (C.5b) we raise (lower) the measured total cost of capital for all firms in our analysis by 15%.

Table C.6a
Setting $\eta_K = 0$ with TFPQ1 — 1996–2012.

Industry	1996	1998	2000	2002	2004
	ΔTFP	ΔTFP	ΔTFP	ΔTFP	ΔTFP
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

Industry	2006	2008	2010	2012
	ΔTFP	ΔTFP	ΔTFP	ΔTFP
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 C.6b
Setting $\eta_Y = 0$ with TFPQ1 — 1996–2012.

Industry	1996	1998	2000	2002	2004
	ΔTFP	ΔTFP	ΔTFP	ΔTFP	ΔTFP
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

Industry	**2006**	**2008**	**2010**	**2012**
	ΔTFP	ΔTFP	ΔTFP	ΔTFP
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 C.6c
Setting $\phi = 0$ with TFPQ1 — 1996–2012.

Industry	1996	1998	2000	2002	2004
	ΔTFP	ΔTFP	ΔTFP	ΔTFP	ΔTFP
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

Industry	2006	2008	2010	2012
	ΔTFP	ΔTFP	ΔTFP	ΔTFP
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 C.6d
Setting $\phi = 0$ with TFPQ2 — 1996–2012.

	1996	1998	2000	2002	2004
Industry	ΔTFP	ΔTFP	ΔTFP	ΔTFP	ΔTFP
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

Industry	2006	2008	2010	2012
	ΔTFP	ΔTFP	ΔTFP	ΔTFP
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

Table C.7a
Setting $\eta_K = 0$ with TFPQ1.

Revenues netted for interm. inputs			
Industry	**1995**	**2005**	**2014**
	ΔTFP	ΔTFP	ΔTFP
Food-To.	1.010	0.979	0.999
Paper	1.000	1.002	1.011
Chem	1.004	1.000	1.007
Metal	0.989	0.979	1.019
Mach.	1.020	0.996	1.005
Elect	1.031	1.020	1.038
Trans.Eq	1.043	0.940	1.002

Table Notes. Tables C7a–b present counterfactual experiments, where $\eta_K = 0$ (C.7a) or $\eta_Y = 0$ (C.7b) is set for all firms and the resulting counterfactual TFPs are computed for a specification where revenues are netted out for cost of goods sold — a proxy for intermediate goods usage. The reported ΔTFP 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 C.7b
Setting $\eta_Y = 0$ with TFPQ1.

Revenues netted for interm. inputs			
Industry	**1995**	**2005**	**2014**
	ΔTFP	ΔTFP	ΔTFP
Food-To.	1.135	1.603	−2.794
Paper	1.670	1.998	2.028
Chem	1.060	1.279	1.575
Metal	1.142	1.225	1.369
Mach.	0.833	1.165	1.103
Elect	0.893	2.077	1.711
Trans.Eq	0.957	0.914	0.760

Table Notes. Tables C7a–b present counterfactual experiments, where $\eta_K = 0$ (C.7a) or $\eta_Y = 0$ (C.7b) is set for all firms and the resulting counterfactual TFPs are computed for a specification where revenues are netted out for cost of goods sold — a proxy for intermediate goods usage. The reported ΔTFP 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 C.7c
Setting $\phi = 0$ with TFPQ1.

Revenues netted for interm. inputs			
Industry	**1995**	**2005**	**2014**
	ΔTFP	ΔTFP	ΔTFP
Food-To.	1.623	1.592	1.577
Paper	5.071	7.621	7.235
Chem	8.53	8.517	9.357
Metal	3.903	13.458	8.307
Mach.	2.972	3.137	3.300
Elect	1.687	3.179	4.314
Trans.Eq	2.679	2.813	2.846

Table Notes. Tables C7c–d present counterfactual experiments, where $\phi = 0$ with TFPQ1 (C.7c) or $\phi = 0$ with TFPQ2 (C.7d) is set for all firms and the resulting counterfactual TFPs are computed for a specification where revenues are netted out for cost of goods sold — a proxy for intermediate goods usage.

Table C.7d
Setting $\phi = 0$ with TFPQ2.

Revenues netted for interm. inputs			
	1995	2005	2014
Industry	ΔTFP	ΔTFP	ΔTFP
Food-To.	1.484	1.000	1.577
Paper	3.062	5.470	5.260
Chem	6.485	8.415	9.180
Metal	2.308	4.643	7.630
Mach.	2.895	3.132	2.922
Elect	1.630	3.089	4.250
Trans.Eq	2.637	2.137	2.845

Table Notes. Tables C7c–d present counterfactual experiments, where $\phi = 0$ with TFPQ1 (C.7c) or $\phi = 0$ with TFPQ2 (C.7d) is set for all firms and the resulting counterfactual TFPs are computed for a specification where revenues are netted out for cost of goods sold — a proxy for intermediate goods usage.

Table C.8a
Setting $\eta_K = \bar{\eta}_K$.

Industry	1995	2005	2014
	ΔTFP	ΔTFP	ΔTFP
Food-To.	1.000	1.022	1.015
Paper	0.989	1.012	1.021
Chem	1.002	1.006	1.013
Metal	1.002	0.997	1.033
Mach.	0.991	1.021	1.014
Elect	1.007	1.055	1.049
Trans.Eq	1.003	1.024	1.023

Table Notes. Tables C8a–b present counterfactual experiments, where $\eta_K = \bar{\eta}_K$ (C.8a) and $\eta_Y = \bar{\eta}_Y$ (C.8c) is set for all firms – with $\bar{\eta_K}$ (and $\eta_Y = \bar{\eta}_Y$) denoting the average level capital (and output) distortion in a particular industry in a given year – 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 C.8b
Setting $\eta_Y = \bar{\eta}_Y$ with TFPQ1.

Industry	**1995**	**2005**	**2014**
	ΔTFP	ΔTFP	ΔTFP
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 C8a–b present counterfactual experiments, where $\eta_K = \bar{\eta}_K$ (C.8a) and $\eta_Y = \bar{\eta}_Y$ (C.8b) is set for all firms – with $\bar{\eta_K}$ (and $\eta_Y = \bar{\eta}_Y$) denoting the average level capital (and output) distortion in a particular industry in a given year – 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 C.8c
Setting $\phi = \bar{\phi}$ with TFPQ1.

Industry	**1995**	**2005**	**2014**
	ΔTFP	ΔTFP	ΔTFP
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

(*continued on next page*)

Table C.8c (*continued*).

Elect	1.587	2.843	5.662
Trans.Eq	2.635	2.140	2.847

Table Notes. Tables C8c–d present counterfactual experiments, where $\phi = \bar{\phi}$ with TFPQ1 (C.8c) or $\phi = \bar{\phi}$ with TFPQ2 (C.8d) is set for all firms and the resulting counterfactual TFPs are computed — with $\bar{\phi}$ denoting the average level technique distortion in a particular industry in a given year.

Table C.8d
Setting $\phi = \bar{\phi}$ with TFPQ2.

Industry	**1995**	**2005**	**2014**
	ΔTFP	ΔTFP	ΔTFP
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 Notes. Tables C8c–d present counterfactual experiments, where $\phi = \bar{\phi}$ with TFPQ1 (C.8c) or $\phi = \bar{\phi}$ with TFPQ2 (C.8d) is set for all firms and the resulting counterfactual TFPs are computed — with $\bar{\phi}$ denoting the average level technique distortion in a particular industry in a given year.

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