Input-Output Networks and Misallocation*

Jing Hang† Pravin Krishna ‡ Heiwai Tang§

SYSU JHU and NBER HKU

September 3, 2026

Abstract

This paper evaluates the bias in estimating the cost of misallocation resulting from using a value-added framework, relative to one with production networks. The bias has two sources: incorrect aggregation in the value-added model, and incorrect inference of firm productivity and wedges using value-added data. Whether the value-added estimate is biased critically depends on the presence of within-sector intermediate input distortions. Without such distortions, the bias is zero. With them, the value-added estimate may be biased upward or downward. Conditional on the joint distribution of productivity and other wedges, a local approximation links greater dispersion of intermediate input distortions to a larger absolute bias. Empirically, we find both positive and negative biases in Chinese and Indian firm-level data. The bias is much smaller in Chinese data than in Indian data, consistent with China's smaller within-sector dispersion of intermediate-input distortions. We also show that inconsistent calibration of the value-added parameters creates an additional source of bias.

*We thank Robert Feenstra, Hugo Hopenhayn, Chang-Tai Hsieh, Pete Klenow, Sam Kortum, Ernest Liu, Gianmarco Ottaviano, Diego Restuccia, Michael Song, Chad Syverson, Felix Tintelnot, Johannes Van Biesebroeck, Daniel Xu, Xiaodong Zhu, and seminar/conference participants at CEPR Conference on Global Value Chains, Trade and Development, Columbia University, Fudan University, Hitotsubashi University, NBER China Meeting, Peking University, Stanford, UC Berkeley, and UC Davis for comments. We are especially grateful to several anonymous reviewers for comments that greatly improved the paper. Hang thanks the National Natural Science Foundation of China (Grant No. 72573190) for financial support. Of course, all errors are our own.

†Email: hangj5@mail.sysu.edu.cn.

‡Email: krishna@jhu.edu.

§Email: tangecon@hku.hk.

1 Introduction

A vast literature, pioneered by Restuccia and Rogerson (2008) and Hsieh and Klenow (2009), studies how resource misallocation across heterogeneous firms could lower aggregate productivity.[1] In particular, Hsieh and Klenow (2009) (HK hereafter) develop an accounting framework to estimate the cost of resource misallocation from market frictions and policy distortions using firm-level data. Subsequent contributions to the literature have identified reasons why their estimates may be systematically biased. Jones (2011, 2013) have posited that ignoring inter-sectoral linkages in production, as HK do, may understate the cost of misallocation because production networks amplify the effects of within-sector distortions. This argument, however, does not account for a related change in measurement: in a model with inter-sectoral linkages, the appropriate output concept is gross output instead of value added. Gandhi et al. (2017) find that firms' physical total factor productivity (TFP) is substantially less dispersed when measured from gross-output data than from value-added data, implying that the value-added approach may instead overstate the cost of misallocation.

This paper studies the relevance of these arguments about the quantitative assessment of aggregate TFP losses resulting from resource misallocation. We present a complete evaluation of the bias from using a value-added framework by incorporating the insights of both Jones (2011, 2013) and Gandhi et al. (2017) in one analysis.[2]

We first approach the question theoretically. For this purpose, we develop a gross-output approach (the GO approach) by incorporating an inter-sectoral input-output (IO) network into the HK framework. Taking this model as the true data generating process, we evaluate the bias in measuring the cost of misallocation using the HK approach (the VA approach),

[1] This literature also includes Banerjee and Duflo (2005), Alfaro et al. (2009), Guner et al. (2008), Buera and Shin (2013), and Bartelsman et al. (2013), among many others. See Restuccia and Rogerson (2013), Hopenhayn (2014), and Ghatak and Mookherjee (2025) for reviews.

[2] To compare with HK, we focus on the percentage gain in aggregate TFP (efficiency) from removing distortions. That is, we evaluate efficient TFP relative to actual TFP. This is the inverse of the TFP loss from misallocation, which evaluates actual TFP relative to efficient TFP. We sometimes use TFP/efficiency loss when there is no confusion.

with value added measured as gross output minus expenditure on intermediate inputs.[3] Moving from the GO approach to the VA approach entails two changes in our analysis: abstracting from intersectoral linkages, and changing the concept of output. It turns out that uniting the two aspects in one analysis leads to new insights regarding the bias of the VA approach.

We identify two sources of bias when the VA approach is used to evaluate the cost of misallocation: 1) incorrect aggregation in the VA model; and 2) incorrect inference of firm productivity and wedges using value-added data. Whether the VA approach is biased depends critically on the presence of within-sector intermediate input distortions. Without such distortions, the VA approach correctly aggregates firm-level distortions and the inference of firm productivity and wedges using value-added data is unbiased. The VA approach thus does not have a tendency to systematically bias the measurement of misallocation, in contrast to Jones (2011, 2013) and Gandhi et al. (2017) who only focus on one aspect of the differences between the two approaches. The intuition behind the finding is that value-added measures implicitly incorporate the amplification effect of inter-sectoral linkages, which is revealed in the data as a more dispersed distribution of value-added productivity. Without intermediate input distortions, the network amplification and the smaller dispersion of firm productivity completely offset each other, leaving the TFP gain from removing distortions the same in both approaches.

When within-sector intermediate input distortions are present, this equivalence breaks down. Both aggregation and inference contribute to the VA bias, which depends nonlinearly on the joint distribution of firm productivity and input distortions. The direction of the bias is generally ambiguous. A local approximation of the bias nevertheless links its absolute size, conditionally, to the dispersion of intermediate-input distortions. These are the two theoretical predictions that we examine in the data.

We evaluate the potential biases in the assessment of the cost of misallocation using Chi-

[3]We use "approach" to denote the full procedure of applying a model to data, and "model" to denote only the theoretical structure.

nese and Indian industrial enterprise data. Interestingly, using the Chinese Annual Survey of Industrial Production (1998-2007), we find that the two approaches produce very similar measured TFP gains from the removal of all distortions. The average difference in the estimated TFP gains under the two approaches is less than 10 percentage points, compared to the average TFP gain of about 161% under the GO approach. The aggregate TFP gain under the VA approach can be smaller or larger than that under the GO approach. At the sector level, close to half of the sector-year observations have a positive VA bias. For India, however, based on the Indian Annual Survey of Industries (1999-2008), we find substantially larger TFP gains from removing all distortions under the GO approach than under the VA approach. The difference averages around 28 percentage points, with the average TFP gain estimated under the GO approach at 62%. Nevertheless, there are still around 3% of sector-year observations with a positive bias.

Our findings of VA bias in both directions and smaller absolute bias in China are robust to alternative calibrations of the production function parameters. The small VA bias in China appears to be consistent with its smaller dispersion of intermediate input distortions. The variance of the intermediate input distortions (in logs) is only about 0.03, compared to 0.52 for primary inputs (a weighted average of capital and labor) in China. On the other hand, for India, the variance of the intermediate input distortions equals 0.29, while that of the primary input distortion is only 0.45. These findings thus provide empirical support for our theoretical characterization of the bias.

Our calibration of the elasticity of substitution and sectoral weights is consistent with the theoretical mapping between the two models. The common practice of calibrating these VA parameters, however, often deviates from their theoretical counterparts, leading to additional biases. First, the literature often calibrates the elasticity of substitution using GO estimates. Our theoretical analysis suggests that the VA elasticity should be much smaller than the GO estimates. Imposing HK's baseline elasticity in both models, we find that China's aggregate TFP gains in the VA model increase significantly, implying a substantial upward bias. For

India, the implied TFP gain in the VA model also increases, reducing the downward bias of the VA estimates. These findings highlight the importance of choosing the right elasticity in calibrating models with different concepts of output.

Second, VA studies often calibrate sectoral weights to sectoral value-added shares of GDP. But between-sector distortions in intermediate inputs can make these shares differ from the weights implied by the GO model. In China, incorrect calibration of sectoral weights significantly lowers the VA estimates, as the value-added shares of gross output are much lower in China than in the US, which are our calibration targets for the production function parameters. In India it raises the VA estimates, because the VA shares of gross output are slightly larger than in the US. Miscalibrated sectoral weights therefore can also bias the VA estimates in either direction.

This paper contributes to three interrelated strands of literature. First, it contributes to the growing literature on resource misallocation, in particular studies that complement and extend the analysis of HK.[4] Important studies along this line include Asker et al. (2014) and David and Venkateswaran (2019), who allow for dynamic capital adjustment; Bartelsman et al. (2013), who introduce fixed costs to production; and Song and Wu (2015) and Gollin and Udry (2021), who allow for technology heterogeneity. Compared to this line of work, our study builds on Jones (2011, 2013) and Gandhi et al. (2017) to present a complete evaluation of the bias from using a value-added framework. A few studies (Dias et al., 2016; Bils et al., 2021; Wang and Xu, 2025) also introduce intermediate inputs into the HK framework and find a discrepancy between the VA estimates and the estimates with intermediate inputs. Their focus, however, is not a systematic evaluation of the VA approach. Using a value-added framework can be viewed as a measurement problem. In this sense, our study is also related to another line of research that tries to distinguish measurement errors from misallocation (Dong, 2011; Song and Wu, 2015; Haltiwanger et al., 2018; Gollin and Udry,

[4]The HK framework has been widely used in the literature. Notable examples include Kalemli-Ozcan and Sorensen (2012), Ziebarth (2013), Brandt et al. (2013), Oberfield (2013), Hsieh and Klenow (2014), Chen and Irarrazabal (2015), Gopinath et al. (2017), Adamopoulos et al. (2022), and Chen et al. (2022).

2021; Bils et al., 2021). These studies are driven by measurement issues in the data, while we focus on a conceptual issue of measurement.

Second, in exploring the role of intersectoral linkages, this paper contributes to the literature on production networks. Besides Jones (2011, 2013), it is also related to several other recent papers on the network propagation of distortions, including, among others, Bartelme and Gorodnichenko (2015), Caliendo et al. (2022), Bigio and La'O (2020), Liu (2019), Luo (2019), Baqaee and Farhi (2019a,b, 2020), Altinoglu (2021), and Osotimehin and Popov (2023). While these studies mainly focus on the aggregate effects of idiosyncratic distortions in production networks, we pay close attention to the comparison of a GO approach to a VA approach in measuring the cost of misallocation. In this sense, our theoretical analysis resembles the seminal work of Hulten (1978) who establishes the link between the GO approach and the VA approach to growth accounting.

Third, our study of the bias of the VA model echoes an earlier literature on the validity of the concept of real value added (Sato, 1976; Bruno, 1978). Bruno (1984) and Basu and Fernald (1995, 1997, 2002) have shown that using value-added measures can lead to biased results in different scenarios, such as the estimation of productivity growth and returns to scale. Recently, Bridgman and Herrendorf (2021) discuss how the use of different output concepts affects the measurement of sectoral markups. In the structural transformation literature, Herrendorf et al. (2013) discuss how different views of sectors, either as categories of final expenditure or value added, require corresponding changes in the specification of preferences. Different from these studies, this paper evaluates the bias of using a value-added framework in measuring misallocation across heterogeneous firms, resulting in new insights into the bias of VA estimates of misallocation and into the mapping of VA parameters.

The rest of the paper is structured as follows. Section 2 presents the two approaches for measuring the cost of misallocation. Section 3 discusses the two sources of bias in the VA approach. Section 4 first characterizes the bias theoretically, and then evaluates it in Chinese and Indian data. Section 5 concludes.

2 Two Theoretical Approaches

This section introduces the two theoretical approaches to measuring misallocation. We first introduce the GO approach, which adds a production network *à la* Long and Plosser (1983) to the HK framework. We then briefly sketch the VA approach for notational purposes.

2.1 The Gross Output (GO) Approach

There are S sectors in the economy. Sectoral output Q_s is used either as intermediate input M_s or for final consumption C_s. A final product Y is produced by a representative firm with a Cobb-Douglas technology,

$$Y = \prod_{s=1}^{S} C_s^{\theta_s}, \text{ with } \sum_{s=1}^{S} \theta_s = 1. \tag{1}$$

Let the final output be the numeraire. The demand for sectoral output from the final good producer is $P_s C_s = \theta_s Y$. Market clearing for sectoral output implies,

$$Q_s = C_s + M_s, \tag{2}$$

where $M_s = \sum_{q=1}^{S} M_{sq}$ with M_{sq} being the demand from sector q for the output of sector s. The sectoral output itself is produced using differentiated intermediate varieties Q_{si},

$$Q_s = \left(\sum_{i=1}^{N_s} Q_{si}^{\frac{\sigma_s - 1}{\sigma_s}} \right)^{\frac{\sigma_s}{\sigma_s - 1}}, \tag{3}$$

where N_s is the total number of varieties in sector s and σ_s is the sector-specific elasticity of substitution. The inverse demand for a variety is given by $P_{si} = P_s Q_s^{\frac{1}{\sigma_s}} Q_{si}^{-\frac{1}{\sigma_s}}$, with the sectoral price index $P_s = \left(\sum_{i=1}^{N_s} P_{si}^{1-\sigma_s} \right)^{\frac{1}{1-\sigma_s}}$.

Each variety is produced by a monopolistically competitive firm using two primary inputs, capital and labor, together with intermediate inputs from all sectors. The production

technology is Cobb-Douglas,

$$Q_{si} = A_{si}\left(K_{si}^{\alpha_s} L_{si}^{1-\alpha_s}\right)^{\eta_s}\left(\prod_{q=1}^{S} M_{qsi}^{\lambda_{qs}}\right)^{1-\eta_s}, \text{ with } \sum_{q=1}^{S}\lambda_{qs} = 1. \tag{4}$$

Firms face idiosyncratic market and/or policy distortions, which manifest as reduced-form wedges in their input use. Taking technology and demand as given, each firm solves the following profit maximization problem,

$$\max_{Q_{si},K_{si},L_{si},\{M_{qsi}\ \forall q\}} \pi_{si} = P_{si}Q_{si} - (1+\tau_{Ksi})RK_{si} - (1+\tau_{Lsi})WL_{si} - (1+\tau_{Msi})\sum_{q=1}^{S} P_q M_{qsi}.$$

Following HK, we assume that the wedges distort firms' input decisions without consuming resources.[5] A stand-in for the wedges is taxes and subsidies fully rebated to households. They could also be viewed as shadow prices for firm-level constraints, such as a collateral constraint for renting capital.

We solve the model in two stages: first the within-sector problem and then the between-sector problem. Because both problems are standard, the main text directly states the results, with proofs of key results relegated to Online Appendix A. The following lemma shows that sectoral production inherits the structure of the firm production function.

Lemma 1 *Taking sectoral inputs as given, the sectoral production function is given by,*

$$Q_s = TFP_s \cdot \left(K_s^{\alpha_s} L_s^{1-\alpha_s}\right)^{\eta_s}\left(\prod_{q=1}^{S} M_{qs}^{\lambda_{qs}}\right)^{1-\eta_s}, \text{ and } TFP_s = \left[\sum_{i=1}^{N_s}\left(A_{si}\frac{TFPR_s}{TFPR_{si}}\right)^{\sigma_s-1}\right]^{\frac{1}{\sigma_s-1}}, \tag{5}$$

where $K_s = \sum_{i=1}^{N_s} K_{si}$ *and* $L_s = \sum_{i=1}^{N_s} L_{si}$ *are capital and labor employed by the sector.*

[5] Such distortions correspond to the type of distortions without discarded payments discussed by Bigio and La'O (2020). Bigio and La'O (2020) show that when wedges represent discarded payments, they are isomorphic to productivity shocks. Because we do not observe output lost to distortions in the data, we assume firm productivity A_{si} already incorporates such wedges.

Sectoral and firm revenue productivity (TFPR) are defined as,

$$TFPR_s \equiv \frac{P_s Q_s}{\left(K_s^{\alpha_s} L_s^{1-\alpha_s}\right)^{\eta_s} \left(\prod_{q=1}^{S} M_{qs}^{\lambda_{qs}}\right)^{1-\eta_s}}, \tag{6}$$

$$TFPR_{si} \equiv \frac{P_{si} Q_{si}}{\left(K_{si}^{\alpha_s} L_{si}^{1-\alpha_s}\right)^{\eta_s} \left(\prod_{q=1}^{S} M_{qsi}^{\lambda_{qs}}\right)^{1-\eta_s}}. \tag{7}$$

As shown in HK, firm TFPR is a weighted sum of marginal revenue products (MRPs), which varies between firms only because of the distortions. Firm TFPR thus summarizes the impact of distortions on each firm. We postpone the discussion of MRPs to the next section, where we discuss the inference of wedges.

Before proceeding, we define two objects that are key to aggregation. The Domar weight, $v_s = \frac{P_s Q_s}{Y}$, is simply the sectoral sales-to-GDP ratio (Domar, 1961). The vector of Domar weights V can be solved as,

$$V = \left(I - B \cdot \text{diag}(\mathcal{T}_M^{\circ -1})\right)^{-1} \theta,$$

where θ is the vector of sectoral shares in final consumption, B is the direct requirement matrix with its element given by $b_{sq} = \lambda_{sq}(1-\eta_q)$, $\mathcal{T}_M$ is the vector of $\mathcal{T}_{Ms} = (1-\eta_s)\lambda_{qs}\frac{P_s Q_s}{P_q M_{qs}}, \forall q$, summarizing the intermediate input distortions within a sector,[6] diag$(\cdot)$ transforms a vector into a diagonal matrix, and $\circ - 1$ is the element-wise Hadamard inverse. If there are no distortions in the network, namely $\mathcal{T}_{Ms} = 1$ for all sectors, we define $\tilde{V} \equiv (I - B)^{-1}\theta$ as the influence vector in Acemoglu et al. (2012), which captures how sectoral productivity shocks propagate downstream to other sectors through the production network.[7] We denote its element to be $\tilde{v}_s$.

Aggregation in this economy is stated in the following proposition.

[6] $\mathcal{T}_{Ms}$ is related to firm-level distortions according to $\mathcal{T}_{Ms} = \frac{1}{\sum_i \frac{\sigma_s - 1}{\sigma_s} \frac{P_{si} Q_{si}}{P_s Q_s} \frac{1}{1+\tau_{Msi}}}$.

[7] This requires us to remove distortions due to market power besides the input wedges.

Proposition 1 *The economy admits an aggregate production function given by,*

$$Y = AK^{\alpha}L^{1-\alpha}, \tag{8}$$

with $\alpha = \sum_{s=1}^{S} \tilde{v}_s \alpha_s \eta_s$ *and total factor productivity given by,*

$$A = \gamma \prod_{s=1}^{S} (TFP_s)^{\tilde{v}_s}. \tag{9}$$

In this Cobb-Douglas economy, distortions have no effect on the shape of the production function. The output elasticity of capital in the aggregate production function is an average of the sectoral output elasticities weighted by the influence vector. The term γ summarizes the effect of between-sector distortions. A previous version of the paper (Hang et al., 2020) contains a breakdown of this term. In this paper, we focus on within-sector misallocation, given by the second term: the weighted average of sectoral TFP.[8] Due to the presence of distortions, Hulten's theorem (Hulten, 1978) no longer holds: The output elasticity of sectoral TFP is given by the influence vector instead of the Domar weights.

Letting Y^E be the efficient output, we measure the cost of misallocation as the output gains from moving to efficient allocation, given as follows,

$$\left(\frac{Y^E}{Y}\right)^{o} = \prod_{s=1}^{S} \left(\frac{TFP_s^E}{TFP_s}\right)^{\tilde{v}_s}, \tag{10}$$

where $TFP_s^E = \left[\sum_{i=1}^{N_s} A_{si}^{\sigma_s - 1}\right]^{\frac{1}{\sigma_s - 1}}$ is efficient sectoral TFP. The aggregate output gain thus equals the geometric sum of sectoral TFP gains weighted by the influence vector. Applying the measure to data is straightforward if we can measure firm productivity and wedges from data, given the model parameters. We discuss the measurement of these objects in the next

[8] While between-sector misallocation is equally important, we do not study it in this paper as between-sector studies often employ different data and methodology from within-sector studies. Online Appendix D contains a brief discussion of measuring between-sector misallocation using the VA approach. It shows that the VA approach has a tendency to underestimate the cost of misallocation.

section.

2.2 The Value-Added (VA) Approach

We next briefly introduce the VA approach, which is essentially the original HK approach. The purpose here is to introduce some notation and results for future reference.

The single final product is produced with sectoral value-added, $Y = \Phi \prod_{s=1}^{S} Y_s^{\widehat{\theta}_s}$, with $\sum_{s=1}^{S} \widehat{\theta}_s = 1$. Φ is a normalizing constant to ensure that final products in the two models are measured in the same unit. We use a hat as notation to indicate a VA variable that is different from its GO counterpart. Sectoral value added is a CES aggregate over its varieties (Y_{si}), with the elasticity of substitution $\widehat{\sigma}_s$.

Each firm has a value-added production function, using primary inputs only, $Y_{si} = \widehat{A}_{si} K_{si}^{\widehat{\alpha}_s} L_{si}^{1-\widehat{\alpha}_s}$. The firms face idiosyncratic wedges in using these inputs (τ_{Ksi} and τ_{Lsi}),[9] which are the same as in the GO model. Using a value-added framework should not affect the size of the distortions.[10] Input prices (R and W) too are not distinguished between the two models: they should remain the same if both models can rationalize the same data.

The aggregate production function in this model has the same Cobb-Douglas form as that in the GO model, $Y = \widehat{A} K^{\widehat{\alpha}} L^{1-\widehat{\alpha}}$, where the capital share is $\widehat{\alpha} = \sum_{s=1}^{S} \widehat{\theta}_s \widehat{\alpha}_s$, and total factor productivity can also be decomposed into a within-sector and a between-sector component,

$$\widehat{A} = \Phi \hat{\gamma} \prod_{s=1}^{S} \left(\widehat{TFP}_s \right)^{\widehat{\theta}_s}. \tag{11}$$

Sectoral TFP in the VA model also has the same form as that in the GO model, except that

[9] A minor difference from HK is that they assume an output and a capital wedge while we assume a capital and a labor wedge. The assumption simplifies the algebra a little but will not affect the results in any way. The wedges change the MRPs. Because there are three possible wedges but only two inputs, we can match the same MRPs with different sets of wedges. It also means that the wedges have no structural interpretations. In this paper, when we say intermediate input distortions, we actually mean any product or input market frictions that would distort a firm's use of intermediate input.

[10] However, inferred wedges from data might be different in these two models, depending on whether there are intermediate input distortions. We will discuss the inference in Section 3.2.

now TFPR and TFPQ are expressed in terms of the value-added measures,

$$\widehat{TFP}_s = \left[\sum_{i=1}^{N_s}\left(\widehat{A}_{si}\frac{\widehat{TFPR}_s}{\widehat{TFPR}_{si}}\right)^{\widehat{\sigma}_s-1}\right]^{\frac{1}{\widehat{\sigma}_s-1}}. \tag{12}$$

The output/TFP gain from moving to efficient allocation is again the weighted geometric average of sectoral TFP gains,

$$\left(\frac{Y^E}{Y}\right)^{va} = \prod_{s=1}^{S}\left(\frac{\widehat{TFP}_s^E}{\widehat{TFP}_s}\right)^{\widehat{\theta}_s}, \text{ with } \widehat{TFP}_s^E = \left[\sum_{i=1}^{N_s}\hat{A}_{si}^{\hat{\sigma}_s-1}\right]^{\frac{1}{\hat{\sigma}_s-1}}. \tag{13}$$

Applying the measure to data, however, requires firm productivity and wedges that are inferred from value-added data.

3 Sources of Bias in the VA Approach

Because firms use both primary and intermediate inputs in reality, the GO model provides a natural representation of the production process in an economy. The VA model is an abstraction that removes intersectoral linkages. Applying the VA model to data, however, also requires a change in the output concept from gross output to value added. The VA approach therefore is not merely the GO model without intermediate inputs. It represents another way to view the production process. In the structural transformation literature, Herrendorf et al. (2013) have shown that the sectors can be viewed as producing either final consumption or value added, provided the model is specified consistently with the chosen output concept.

The value-added representation is only valid under particular restrictions (Bruno, 1978). This section identifies those restrictions for measuring misallocation using a value-added framework. For this purpose, we conduct a thought experiment by taking the GO model as the true data generating process, and applying both approaches to the same data. The

resulting comparison isolates the sources of bias in the VA approach.

To apply the VA approach, we follow the convention of defining value added as revenue minus expenditure on intermediate inputs,

$$P_{Ysi}Y_{si} = P_{si}Q_{si} - \sum_{q=1}^{S} P_q M_{qsi} \tag{14}$$

This is the measurement equation that we use in this paper. The key assumption is that the intermediate input distortions are not recorded in the prices paid by the firms. This assumption restricts the class of distortions covered by our study. Shadow prices for firm's financial constraints satisfy this condition, as do taxes/subsidies when inputs are measured net of them. The assumption excludes firm-level intermediate input price differences induced by trade credit, as discussed in Luo (2019), even though such price differences do not consume real resources. Because we only observe expenditure on intermediate inputs but not their quantity,[11] distortions recorded as firm-specific prices would leave input quantity unobserved.[12] Online Appendix C shows that when recorded and unrecorded distortions are multiplicative, violating the assumption biases both approaches to the same extent and therefore leaves the comparison between them unchanged.

Applying either approach involves two steps: inferring firm productivity and wedges, and aggregating these objects into an aggregate gain using equations 10 or 13. Each step could contribute to biased estimates. We next discuss aggregation first and inference second. In the following discussion, the sectoral and aggregate model parameters are treated as known so that the analysis isolates the issues in model specification. Identifying the model parameters remains important for measuring misallocation, as Section 4.2 illustrates, but it is distinct from choosing the accounting framework.

[11] An exception is Atalay (2014), who observes firm-specific prices of intermediate inputs in a detailed dataset from the US Census Bureau.

[12] HK make an analogous assumption when measuring capital stock from the value of total assets. Applying a common deflator would produce a biased capital measure if firms valued assets at different prices.

3.1 Aggregation in the VA Model

We first ask if the VA model correctly aggregates given distortions such that it would lead to unbiased estimates of TFP gains. Specifically, can its productivity and parameters be chosen so that it yields the same aggregate gain as the GO model? This requires the VA model to rationalize the GO allocation under two different sets of wedges: the existing one and the one with zero wedges. Our analysis thus focuses on specifying the VA parameters that would rationalize the GO allocation under any given wedges, which in turn leads to the condition for correct aggregation in the VA model.

It turns out that correct aggregation in the VA model critically depends on the following assumption.

Assumption 1 $\tau_{Msi} = \mathcal{T}_{Ms}, \ \forall \ s \in \{1, 2, ...S\}$ *and* $i \in \{1, 2, ...N_s\}$.

Assumption 1 allows a sector-specific intermediate input wedge but rules out variation in that wedge across firms within a sector. Proposition 2 shows that this condition is both sufficient and necessary for correct aggregation in the VA model, and gives the corresponding configuration of the VA parameters.

Proposition 2 *Under Assumption 1, the two models have the same allocation of primary inputs, and produce the same aggregate TFP gain, if the following conditions hold: (1)* $\widehat{A}_{si} \propto A_{si}^{\frac{1}{\eta_s}}$, *(2)* $\widehat{\alpha}_s = \alpha_s$, *(3)* $\widehat{\sigma}_s = 1 + \eta_s(\sigma_s - 1)$, *and (4)* $\widehat{\theta}_s = \eta_s \tilde{v}_s$. *If Assumption 1 does not hold, no single parameterization of the VA model can reproduce the GO allocation and TFP gain for all possible wedge configurations.*

The first part of this proposition presents an exact mapping between the two models, reconciling two forces emphasized separately in the literature. First, production networks amplify sectoral productivity changes, which tends to make the GO gain larger. Proposition 1 captures this mechanism through the larger weight placed on sectoral TFP in the GO model. Second, productivity inferred from value-added data is more dispersed (Gandhi et al., 2017), which tends to make the VA gain larger. Under Assumption 1, Proposition

2 shows that the two forces offset exactly: value-added measures incorporate the network amplification through a greater dispersion of measured firm productivity.

The mapping also implies that the elasticity of substitution must change with the output concept, $\widehat{\sigma}_s = 1 + \eta_s(\sigma_s - 1)$. The value-added studies have often chosen the elasticity based on elasticities estimated for gross output instead of value added. HK, for example, cite Broda and Weinstein (2006) and Hendel and Nevo (2006) for their choice of the elasticity, both of which estimate gross-output elasticities. Let us consider the more reasonable case of $\sigma_s > 1$ for gross output. The mapped VA elasticity should be set at a value smaller than the GO elasticity.[13] If we set the GO elasticity to be 3, the conservative value chosen by HK, the corresponding VA elasticity is 2 when $\eta_s = 0.5$, a reasonable number according to Jones (2011). Because measured cost of misallocation rises with the elasticity, miscalibrating this elasticity in value-added studies tends to overstate the cost of misallocation, a point that has not been appreciated enough in the literature.

Although Assumption 1 is unlikely to hold in data (Liu, 2019; Bigio and La'O, 2020), the isomorphism established in Proposition 2 presents a benchmark against which the VA bias can be understood. The second part of Proposition 2 shows that once intermediate input allocation is distorted across firms within a sector, the VA model will be biased due to incorrect aggregation.

3.2 Inference of Firm Productivity and Wedges

The preceding subsection treats firm productivity and wedges as known. In empirical applications, these objects must be inferred from observed output and inputs. We now show how using value-added data changes that inference, and isolate another source of the VA bias.

Imagine we have a firm-level dataset with information on nominal output ($P_{si}Q_{si}$), capital

[13] The economic reason behind the difference in the elasticity is as follows. A one-percent increase in output productivity lowers the firm's output price by one percent, holding input prices fixed. In the VA model, the corresponding changes in productivity and price are $\frac{1}{\eta_s}$ percent. The price response raises primary input demand by $\sigma_s - 1$ percent in the GO model, and $\frac{1}{\eta_s}(\widehat{\sigma}_s - 1)$ in the VA model. Equating the input-demand responses gives the mapping between the elasticities.

(K_{si}), labor (L_{si}), and expenditure on intermediate inputs ($\sum_{q=1}^{S} P_q M_{qsi}$).[14] Using the firm's first-order condition for intermediate inputs, nominal value added is related to nominal gross output according to,

$$P_{Ysi}Y_{si} = \left(1 - \frac{\sigma_s - 1}{\sigma_s}\frac{1-\eta_s}{1+\tau_{Msi}}\right) P_{si}Q_{si}. \tag{15}$$

This condition is pivotal for the results in this subsection. It shows why the inference changes: with intermediate input distortions, the share of value added in gross output deviates from the contribution of primary inputs.[15]

We first discuss the inference of the wedges. For the GO model, the first-order conditions for firms imply,[16]

$$\begin{aligned}
\frac{\sigma_s - 1}{\sigma_s}\frac{\alpha_s \eta_s P_{si}Q_{si}}{RK_{si}} &= 1 + \tau_{Ksi}, \\
\frac{\sigma_s - 1}{\sigma_s}\frac{(1-\alpha_s)\eta_s P_{si}Q_{si}}{WL_{si}} &= 1 + \tau_{Lsi}, \\
\frac{\sigma_s - 1}{\sigma_s}\frac{(1-\eta_s) P_{si}Q_{si}}{\sum_{q=1}^{S} P_q M_{qsi}} &= 1 + \tau_{Msi},
\end{aligned}$$

where R and W are common input prices.[17] The left-hand side is the ratio of MRPs to input prices, and the right-hand side is inferred firm-level wedges expressed in terms of true distortions. The wedges are thus identified as differences in MRPs. For the VA model, we

[14] Most firm-level databases only provide the total value of intermediate inputs. We can further attribute it to different inputs using the model's input-output structure. This is, however, unnecessary for the exercise in this paper.

[15] The deviation also comes from the presence of monopoly rents. Because monopolistic pricing affects all firms proportionally, however, it does not affect the measurement of misallocation.

[16] A few studies have emphasized measurement errors in the data, as mentioned in the introduction. However, the issue of measurement error is independent of that of using the VA approach, which is a conceptual issue. These problems still exist even if we purge out measurement errors.

[17] The exact value of input prices is irrelevant as only the relative size of the wedges matters for measuring misallocation. In practice, we can thus simply normalize these input prices.

can infer the wedges as,

$$\begin{aligned}\frac{\hat{\sigma}_s-1}{\hat{\sigma}_s}\frac{\alpha_s P_{Ysi}Y_{si}}{RK_{si}} &= (1+\tau_{Ksi})\frac{1-\frac{\sigma_s-1}{\sigma_s}\frac{1-\eta_s}{1+\tau_{Msi}}}{1-\frac{\sigma_s-1}{\sigma_s}(1-\eta_s)},\\ \frac{\hat{\sigma}_s-1}{\hat{\sigma}_s}\frac{(1-\alpha_s)P_{Ysi}Y_{si}}{WL_{si}} &= (1+\tau_{Lsi})\frac{1-\frac{\sigma_s-1}{\sigma_s}\frac{1-\eta_s}{1+\tau_{Msi}}}{1-\frac{\sigma_s-1}{\sigma_s}(1-\eta_s)},\end{aligned}$$

where we have used Equation 15. The inferred wedges deviate from the true distortions, because the value-added share of gross output does not measure the true contribution of primary inputs. If Assumption 1 holds, the wedges are correctly inferred up to a constant, which does not affect the measurement of misallocation.

Because firm-level prices are typically unavailable, identifying a firm's physical productivity is more challenging. The CES aggregation at the sector level, however, provides a way to readily link the value of firm output to physical quantity. In the GO model, physical productivity is inferred as,

$$\kappa_s\frac{(P_{si}Q_{si})^{\frac{\sigma_s}{\sigma_s-1}}}{\left(K_{si}^{\alpha_s}L_{si}^{1-\alpha_s}\right)^{\eta_s}\left(\sum_{q=1}^{S}P_qM_{qsi}\right)^{1-\eta_s}}=A_{si}.$$

The left-hand side is observed up to a sector-level constant κ_s, and the right-hand side is true firm productivity. Because the absolute level of firm productivity does not affect resource allocation, we can normalize $\kappa_s=1$. Gross-output productivity can thus be correctly recovered from data. Similarly, physical productivity in the VA model is measured as,

$$\widehat{\kappa}_s\frac{(P_{Ysi}Y_{si})^{\frac{\widehat{\sigma}_s}{\widehat{\sigma}_s-1}}}{K_{si}^{\alpha_s}L_{si}^{1-\alpha_s}}=\left(\frac{1-\frac{\sigma_s-1}{\sigma_s}\frac{1-\eta_s}{1+\tau_{Msi}}}{1-\frac{\sigma_s-1}{\sigma_s}(1-\eta_s)}\right)^{\frac{\widehat{\sigma}_s}{\widehat{\sigma}_s-1}}(1+\tau_{Msi})^{\frac{\eta_s-1}{\eta_s}}A_{si}^{\frac{1}{\eta_s}},$$

where $\widehat{\kappa}_s$ is also a sector-level constant. The right-hand side is inferred value-added productivity, which again is correctly recovered up to a constant when Assumption 1 holds. With intermediate input distortions, inferred value-added productivity, however, deviates from its theoretical counterpart.

The intermediate input wedge affects the inference of VA productivity through two opposing channels. First, it changes the measured value-added share of gross output (the first term): a positive distortion raises the contribution attributed to primary inputs and therefore raises measured VA productivity. Second, it reduces the firm's use of intermediate input and therefore lowers measured VA productivity (the second term). Because these channels have opposite signs, their net effect is ambiguous.

The following proposition summarizes the above discussion.

Proposition 3 *Firm productivity and wedges can be correctly inferred up to a sector-level constant using gross-output data. If Assumption 1 holds, this is also the case for value-added data. Otherwise, the inference using value-added data is biased.*

One way to understand the economics behind the inference problem is to consider our value-added measure as a real value-added measure. An earlier literature has studied the conceptual issues from using real value-added indexes.[18] When the effective price of an intermediate input differs from the market price, subtracting expenditure at the observed market price does not recover the input's productive contribution. The difference between the effective and the market price is then attributed to the value-added measure, which is essentially a partial Solow residual (Basu and Fernald, 1995). The residual then results in mismeasured productivity. The earlier literature focuses mainly on measuring productivity change over time, where changing relative input prices complicate the valuation of intermediate inputs. We instead apply the idea to the comparison across firms, whose effective intermediate input prices differ because of idiosyncratic distortions. In addition, aggregation over heterogeneous firms also introduces new conceptual issues beyond the measurement of firm productivity and MRPs, as discussed in the above subsection.

Sector-level constants do not affect within-sector misallocation. Assumption 1 therefore ensures that the VA approach does not bias the measurement of misallocation. When As-

[18]For example, Bruno (1978) shows that MRPs and productivity are incorrectly inferred using the real value-added index if the intermediate input prices used in constructing the real value-added measures are different from the prices the firms face. See also the discussion in Basu and Fernald (2002).

sumption 1 fails, incorrect inference of firm productivity and wedges becomes a second source of VA bias. Propositions 2 and 3 then imply the following corollary.

Corollary 1 *If Assumption 1 holds and the model parameters are correctly assigned, measurement of misallocation using the VA approach is unbiased relative to that using the GO approach. Otherwise, it is generally biased for both model misspecification and incorrect inference.*

4 Evaluating the Bias of the VA Approach

The preceding section identifies why the VA approach becomes biased when Assumption 1 fails. This section presents an evaluation of that bias. We first present a theoretical characterization of the bias using the exact expression and a local approximation, focusing on the direction and the magnitude of the bias. We then present empirical measures of the bias using firm-level data from China and India. While the empirical findings are of relevance by themselves, we mainly use the empirical exercise as an illustration of the theoretical comparison.

4.1 Theoretical Characterization of the Bias

Because the aggregate TFP gain is a weighted geometric sum of sectoral TFP gains, any remaining error in measuring the aggregate TFP gain comes from mismeasured sectoral gains when the weights are assigned correctly. We therefore focus on a one-sector economy and omit the sector index in this subsection. Because capital and labor wedges are mismeasured in the same way under the VA approach, we simplify the analysis further by retaining labor as the only primary input.

We take firm productivity and wedges in the simplified GO model, $\{A_i, \tau_{Li}, \tau_{Mi}\}$, as firm primitives and express both measured gains in terms of these objects. The next proposition presents an exact characterization of the VA bias.

Proposition 4 *Measured TFP gain from moving to efficiency under the GO approach (in logs) is given by,*

$$L_{GO} = \frac{1}{\eta}\left[\frac{1}{\sigma-1}\log\sum_{i=1}^{N} A_i^{\sigma-1} - \frac{\sigma}{\sigma-1}\log\sum_{i=1}^{N} r_i + \eta\log\sum_{i=1}^{N}\frac{r_i}{1+\tau_{Li}} + (1-\eta)\log\sum_{i=1}^{N}\frac{r_i}{1+\tau_{Mi}}\right],$$

where $r_i = \frac{A_i^{\sigma-1}}{((1+\tau_{Li}))^{\eta(\sigma-1)}(1+\tau_{Mi})^{(1-\eta)(\sigma-1)}}$. *Measured TFP gain under the VA approach (in logs) is given by,*

$$L_{VA} = \frac{1}{\eta(\sigma-1)}\log\sum_{i=1}^{N} A_i^{\sigma-1} d_i^{1+\eta(\sigma-1)}(1+\tau_{Mi})^{(\eta-1)(\sigma-1)} - \frac{1+\eta(\sigma-1)}{\eta(\sigma-1)}\log\sum_{i=1}^{N} r_i d_i + \log\sum_{i=1}^{N}\frac{r_i}{1+\tau_{Li}},$$

where $d_i = \frac{1-\frac{\sigma-1}{\sigma}\frac{1-\eta}{1+\tau_{Mi}}}{1-\frac{\sigma-1}{\sigma}(1-\eta)}$ *measures the share of value added in gross output relative to its undistorted counterpart. The VA bias is then given by,*

$$\begin{aligned} B = L_{VA} - L_{GO} =& \frac{1}{\eta(\sigma-1)}\left(\log\sum_{i=1}^{N} A_i^{\sigma-1} d_i^{1+\eta(\sigma-1)}(1+\tau_{Mi})^{(\eta-1)(\sigma-1)} - \log\sum_{i=1}^{N} A_i^{\sigma-1}\right) \\ &+ \frac{\sigma}{\eta(\sigma-1)}\log\sum_{i=1}^{N} r_i - \frac{1-\eta}{\eta}\log\sum_{i=1}^{N}\frac{r_i}{1+\tau_{Mi}} - \frac{1+\eta(\sigma-1)}{\eta(\sigma-1)}\log\sum_{i=1}^{N} r_i d_i. \end{aligned}$$

The exact expression reproduces Corollary 1 under Assumption 1. Beyond that, however, it is not easy to gauge the size and direction of the VA bias. The bias depends on the whole distribution of firm productivity and wedges in a highly nonlinear way. An important finding emerging from Proposition 4 is that the VA approach is not systematically biased upwards or downwards.

The following simple two-firm example illustrates the sign ambiguity of the VA bias. Let $\sigma = 3$, $\eta = 0.5$, $A = \{1, 1.5\}$, and $\tau_M = (0.4, -0.4)$. When $\tau_L = \{0.4, -0.4\}$, so that the labor wedge is aligned with the intermediate wedge, the TFP gain is 9.57% under the GO approach, and 10.28% under the VA approach. The bias is positive. When the labor wedge is reversed, $\tau_L = \{-0.4, 0.4\}$, the VA approach leads to a negative bias (7.24% vs. 1.16%). This finding is consistent with the zero-bias benchmark under Assumption 1 in that the VA

approach is not systematically biased upwards or downwards.

To gain more insights on the VA bias, we next present a local approximation of the bias. Let $\epsilon z_i = \log(1+\tau_{Mi})$ with fixed and bounded z_i. We can then write d_i as a function of ϵ,

$$d_i = d_i(\epsilon) = \frac{1-ce^{-\epsilon z_i}}{1-c}, \text{ with } c = \frac{\sigma-1}{\sigma}(1-\eta).$$

An increase in ϵ thus increases the absolute size of the intermediate input distortions without changing their alignment with productivity and the labor wedge. Expanding the logarithm of $d_i(\epsilon)$ to second order around $\epsilon = 0$, we have,

$$\log d_i(\epsilon) = \frac{c}{1-c}\epsilon z_i - \frac{c}{2(1-c)^2}\epsilon^2 z_i^2 + O(\epsilon^3).$$

Plugging the approximation into the exact VA bias in Proposition 4, we reach a local second-order approximation of the bias, presented in the next proposition.

Proposition 5 *For given firm productivity and wedges, write $\epsilon z_i = \log(1+\tau_{Mi})$ with fixed and bounded z_i. A local second-order approximation of the bias is given by,*

$$B(\epsilon) = \kappa\epsilon^2[(E_\phi z)^2 - E_\omega(z^2)] + O(\epsilon^3),$$

where $\kappa = \frac{(1-\eta)\sigma}{2\eta(1+\eta(\sigma-1))} > 0$, $E_\phi z = \sum_i^N \phi_i z_i$ *with* $\phi_i = \frac{\frac{A_i^{\sigma-1}}{((1+\tau_{Li}))^{\eta(\sigma-1)}}}{\sum_{i=1}^N \frac{A_i^{\sigma-1}}{((1+\tau_{Li}))^{\eta(\sigma-1)}}}$, *and* $E_\omega(z^2) = \sum_i^N \omega_i z_i^2$ *with* $\omega_i = \frac{A_i^{\sigma-1}}{\sum_{i=1}^N A_i^{\sigma-1}}$.

Ignoring the higher-order term, the local approximation can be decomposed into two economically distinct components,

$$B \approx \kappa\left\{-\operatorname{Var}_\omega(m) + \left[(E_\phi m)^2 - (E_\omega m)^2\right]\right\}, \qquad m_i = \log(1+\tau_{Mi}).$$

where $\operatorname{Var}_\omega(m)$ is the variance of m. The first component is a direct intermediate input reallocation effect. Dispersion in intermediate input distortions creates an efficiency gain in

the GO model from reallocating intermediate inputs across firms, a margin that is absent from the VA approach. This component therefore produces a downward VA bias. The second component is a reweighting effect. It arises because primary input distortions change the weights attached to firms ($\phi_i \neq \omega_i$). When primary and intermediate input distortions are correlated, the VA approach attributes part of the resulting variation in value added to inferred productivity and primary input wedges. If this reweighting moves the weighted mean intermediate input distortion farther from zero, it increases the TFP gain under the VA approach and can overturn the first force. If it moves the weighted mean toward zero, it reinforces the downward bias. Thus, intermediate input distortions alone produce VA underestimation, whereas sufficiently strong sorting between productivity, primary input distortions, and intermediate input distortions can produce VA overestimation.

The local approximation therefore preserves the sign ambiguity of the exact expression. Proposition 5 also establishes a relationship between the size of the bias and that of intermediate input distortions. Holding firm productivity, the labor wedge and the cross-firm pattern z_i fixed, scaling the intermediate input wedge by ϵ scales the VA bias by ϵ^2, no matter the sign of the bias. That is, the absolute size of the bias rises with the dispersion of the intermediate input distortions, for a fixed configuration of the other firm characteristics.

Suppose that $\{\log A_i, \log(1+\tau_{Li}), \log(1+\tau_{Mi})\}$ follows a joint normal distribution. The following corollary expresses the local bias in terms of their variances and correlations, confirming the above findings in a parametric case and leading to further insights.

Corollary 2 *Suppose that firm productivity and input distortions follow a joint log-normal distribution, and* $\log(1+\tau_{Mi})$ *has zero mean, the bias can be further approximated as,*

$$B \approx \kappa[(\sigma-1)^2(\eta^2\rho_{lm}^2\sigma_l^2 - 2\eta\rho_{am}\rho_{lm}\sigma_a\sigma_l) - 1]\sigma_m^2,$$

where σ_x^2 *is the variance of variable* x *and* ρ_{xy} *is the correlation coefficient between variables* x *and* y*, with* x *and* y *belonging to* $\{\log A_i, \log(1+\tau_{Li}, \log(1+\tau_{Mi})\}$.

The log-normal approximation makes the reweighting effect explicit. Three cases are especially informative. First, suppose that the labor wedge is uncorrelated with the intermediate input wedge, $\rho_{lm} = 0$. The bias reduces to,

$$B \approx -\kappa\sigma_m^2 < 0.$$

In this case, labor distortions do not systematically place more weight on firms from either side of the intermediate wedge distribution. The only remaining force is the gain from reallocating intermediate inputs, which is captured by the GO approach but not directly represented in the VA model. The VA approach therefore underestimates the TFP gain.

This result can be reversed when the labor and intermediate input wedges are sufficiently strongly related. Labor distortions affect firms' relative sizes and hence the weights placed on their intermediate input distortions. The VA approach attributes part of the resulting variation in value added to productivity and primary input wedges. If this reweighting places sufficiently large weight on firms from one tail of the intermediate wedge distribution, the VA approach can generate a larger measured TFP gain than the GO approach. A positive bias therefore requires the reweighting effect to be strong enough to dominate the intermediate input reallocation effect. This can be seen clearly if we assume $\rho_{am} = 0$ such that firm productivity and the intermediate input wedge are uncorrelated. The bias reduces to,

$$B \approx \kappa[(\sigma-1)^2\eta^2\rho_{lm}^2\sigma_l^2 - 1]\sigma_m^2.$$

Hence,

$$B > 0 \Leftrightarrow \eta(\sigma-1)|\rho_{lm}|\sigma_l > 1.$$

The relationship between productivity and the intermediate input wedge further determines whether this reweighting effect is reinforcing or offsetting the negative VA bias. If productivity and the intermediate input wedge are correlated in one direction, while the

labor and intermediate input wedges are correlated in the opposite direction ($\rho_{am}\rho_{lm} < 0$), labor distortions move the relevant weighted mean of intermediate input distortions farther from zero. This makes an upward VA bias more likely. If the two correlations have the same sign ($\rho_{am}\rho_{lm} > 0$), labor distortions generally move the weighted mean toward zero and reinforce the downward bias. Thus, productivity heterogeneity does not create the sign reversal by itself. It matters through its interaction with the relationship between primary and intermediate input distortions.

These intuitions help interpret the two-firm example above. In both cases, the more productive firm has the lower intermediate input wedge ($\rho_{am} < 0$). When the labor and intermediate input wedges are aligned ($\rho_{lm} > 0$), the two relevant correlations have opposite signs. The reweighting effect then works against the direct intermediate input effect, and the exact calculation produces a positive VA bias. Reversing the labor wedge changes the sign of this interaction. The reweighting effect then reinforces the direct intermediate input effect, and the VA bias becomes negative. Although the example is neither local nor log-normal, it nevertheless illustrates the same economic mechanism identified by the approximation.

4.2 Empirical Evaluation of the Bias

The theory yields two empirically relevant implications: the VA bias can have either sign, and its local absolute magnitude is linked conditionally to the dispersion of intermediate input distortions. We now use Chinese and Indian firm-level data to illustrate these two points, treating the GO framework as the maintained benchmark. Our exercise is not intended to identify the true level of misallocation, a considerably more demanding task beyond the scope of this paper (Ghatak and Mookherjee, 2025). Instead, we hold the dataset and calibration strategy fixed within each comparison of the two approaches and ask how replacing the GO approach with the VA approach changes the measured TFP gain. The exercise thereby illustrates the bias characterized above and its potential quantitative importance in empirical applications.

Data. We use the Chinese Annual Survey of Industrial Production (1998-2007) and the Indian Annual Survey of Industries (1999-2008). Because these data have been widely used in the literature, including HK, we provide only a brief description here. Online Appendix B.1 provides further details on variable construction and data cleaning.

The Survey of Industrial Production from China's National Bureau of Statistics covers all non-state firms with more than 5 million RMB (about 0.6 million USD during the sample period) in revenue plus all state-owned firms in the industrial sector, which comprises mining, manufacturing, utilities, and construction. We retain only manufacturing firms for our analysis. The Annual Survey of Industries, conducted by the Indian Ministry of Statistics, consists of registered manufacturing plants employing at least 10 workers with power, or at least 20 workers without power. Plants with more than 100 workers are surveyed annually, while all other plants with fewer than 100 workers are randomly sampled. From both datasets, we extract information on the firm's 4-digit industry code, wage bill, output, capital stock, and intermediate input expenditure. To allow for differences in worker human capital across firms, we use wage bill as our measurement of labor input instead of employment.

The number of firms kept growing during our period of investigation. After data cleaning, we are left with 98,100 firms in 1998 and 255,756 firms in 2007 for China. For India, 10,363 firms in 1999 and 20,005 firms in 2008 are included in our sample.

Calibration. Measuring the TFP gains requires values for parameters α_s, η_s, σ_s, and the sectoral weights $\tilde{v}_s$ and $\widehat{\theta}_s$. We calibrate the output elasticities using US input shares matched to Chinese and Indian industries. The US shares are for 6-digit NAICS industries. The output elasticity of capital α_s is calibrated as 1 minus the share of labor income in industrial value-added.[19] To reduce the burden of assigning a different elasticity of substitution to every industry, we set σ_s to be 3 for all industries. The corresponding VA elasticities are then calibrated according to Proposition 2, $\widehat{\sigma}_s = 1 + \eta_s(\sigma_s - 1)$. Because the aggregate share of intermediate inputs in gross output is roughly 0.5 in the US, the resulting VA elasticity

[19] We multiply each US industry's raw labor share by 3/2 to adjust for underreported non-wage benefits in the data.

is around 2, substantially below the GO elasticity. Finally, because our analysis centers on within-sector TFP gains, we simply use the Domar weights to calibrate the sectoral weights for the GO model, and set the VA weights to η_s times the Domar weights. Our calibration of the VA parameters is consistent with Proposition 2, which ensures that the VA bias only comes from model misspecification and inference using value-added data. We discuss the problem of incorrect calibration later. The calibration procedure is summarized in Table 1.

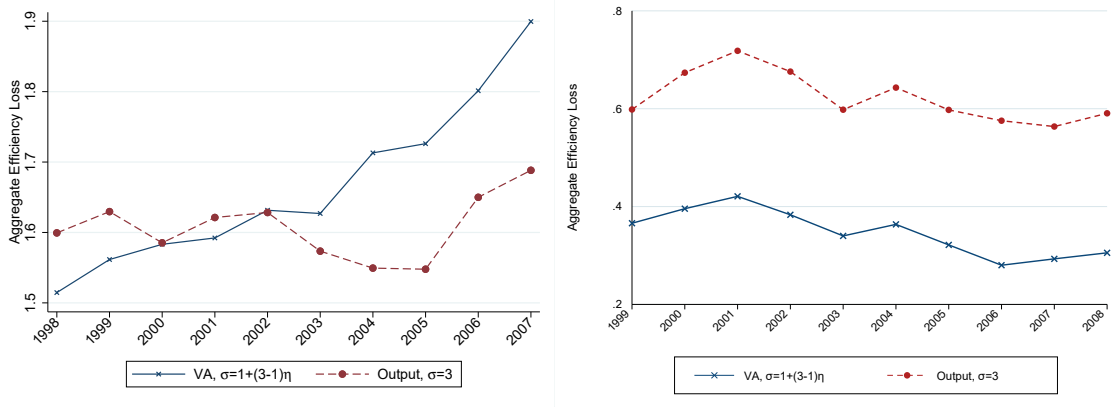
Table 1: Baseline Model Calibration

Parameters	Targeted Value
α_s	1 minus labor's share of value-added for US industries
η_s	Intermediate's share of gross output for US industries
σ_s	3, conservative estimate of the elasticity in the literature
$\widehat{\sigma}_s$	$1+\eta_s(\sigma_s-1)$, according to the theoretical analysis
$\tilde{v}_s$	v_s, industrial output to GDP ratio in Chinese and Indian data
$\widehat{\theta}_s$	$\eta_s v_s$ according to the theoretical analysis

Baseline Results. Figure 1 compares measured aggregate TFP gains under the two approaches. Panel (a) shows that the two approaches give different trends in allocative efficiency for China. There is a clear upward trend in misallocation under the VA approach, while that under the GO approach is roughly flat. Despite the differences, the GO approach does not systematically produce larger or smaller TFP gains than the VA approach. For India, the estimated TFP gains from removing all distortions are always higher under the GO approach. The gap averages 27.6 percentage points over the sample period, compared with an average GO gain of 62.3%, yielding a substantial negative VA bias.

The aggregate results show that the empirical discrepancy between the two approaches can be economically meaningful. The findings for China already confirm our theoretical prediction that the bias could be either downward or upward. Because our theoretical analysis suggests that the bias arises within sectors, we next turn to sector-level measures of the misallocation cost. For comparability, we assume the sectoral weight is 1 for all industries in the GO model and the corresponding VA weight is η_s for each industry. Figure 2 shows

Figure 1: Aggregate TFP Gain in Different Models

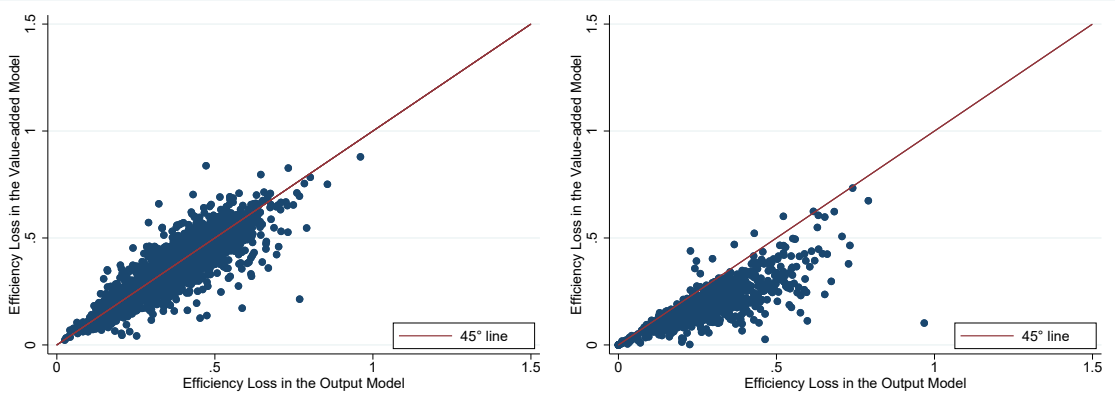


(a) China (b) India

Note: Aggregate TFP gain is defined as $\left(\frac{Y^E}{Y}\right)^o - 1$ and $\left(\frac{Y^E}{Y}\right)^{va} - 1$.

similar sectoral TFP gains under the two approaches in China, with 49% of the sector-year observations showing a positive VA bias. For India, we continue to find significantly larger sectoral TFP gains using the GO approach. Nevertheless, there are still around 3% of observations showing a positive VA bias. Downward and upward biases coexist in both the Chinese and Indian data.

Figure 2: Sectoral TFP Gain in Different Models



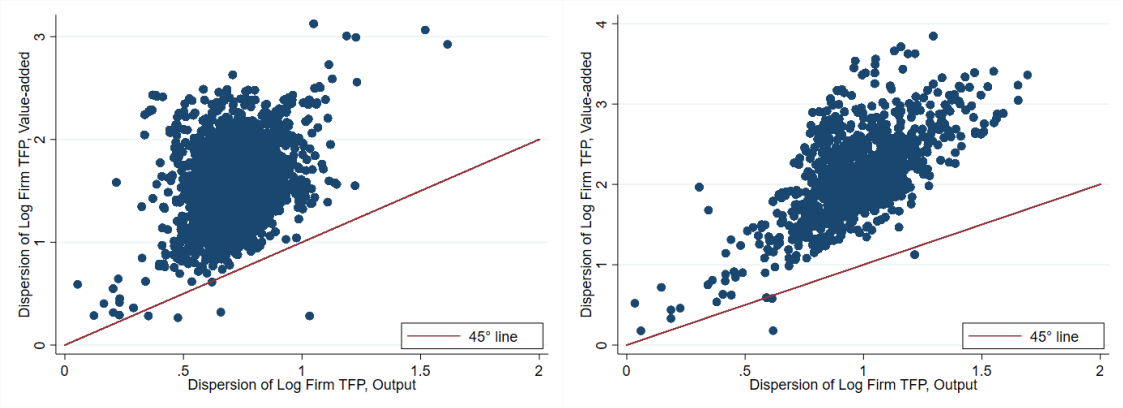
(a) China (b) India

Note: Sectoral TFP gain is measured as $\log\left(\frac{TFP_s^E}{TFP_s}\right)$ and $\log\left(\frac{\widehat{TFP}_s^E}{\widehat{TFP}_s}\right)^{\eta_s}$.

Despite the amplification effect of production networks (Jones, 2011, 2013), the reason

why the TFP gain under the GO approach can be smaller than the VA estimate is a lower dispersion of firm productivity measured in gross-output data (Gandhi et al., 2017). This can be clearly seen from Figure 3, where the standard deviation of log firm TFP measured in gross-output data is plotted against that in value-added data.

Figure 3: Dispersion of Firm Physical Productivity Measured in Different Output Concepts



(a) China (b) India

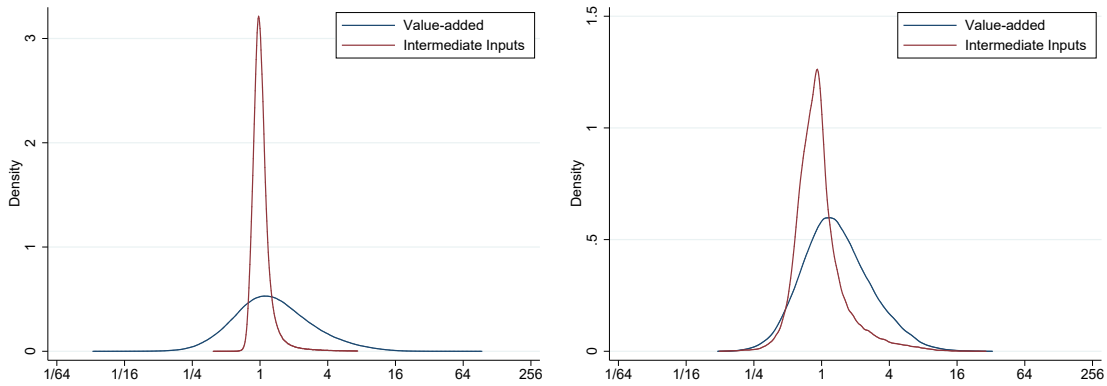
Note: The dispersion is measured by the standard deviation of log firm productivity.

The local approximation suggests a possible explanation for the smaller Chinese discrepancy: intermediate input distortions may be less dispersed in China. Figure 4 examines this mechanism by comparing the distributions of the log MRPs of primary and intermediate inputs, each relative to its industry average.[20] Panel (a) shows that intermediate input MRPs are substantially less dispersed than primary input MRPs in China: their variances are 0.037 and 0.522, respectively. On the other hand, panel (b) shows a much larger dispersion of the MRP of intermediate inputs in India, with the variance reaching 0.289. The variance for the MRPs of primary inputs for India (0.454) is, however, only slightly smaller than that for China. The cross-country pattern is therefore consistent with the local mechanism, although differences in productivity and the joint distribution of the primary input wedges also affect the bias.

Robustness. Because the levels of both gains depend on calibrated production elasticities,

[20] They are given by $\left(\frac{\alpha_s \eta_s P_{si} Q_{si}}{K_{si}}\right)^{\alpha_s} \left(\frac{(1-\alpha_s)\eta_s P_{si} Q_{si}}{L_{si}}\right)^{1-\alpha_s}$ and $\prod_{q=1}^{S} \left(\frac{(1-\eta_s) P_{si} Q_{si}}{P_q M_{qsi}}\right)^{\lambda_{qs}}$.

Figure 4: Dispersion of Marginal Revenue Products



(a) China (b) India

Note: The figures plot the density of the logs of $\left(\frac{\alpha_s \eta_s P_{si} Q_{si}}{K_{si}}\right)^{\alpha_s} \left(\frac{(1-\alpha_s)\eta_s P_{si} Q_{si}}{L_{si}}\right)^{1-\alpha_s}$ and $\prod_{q=1}^{S} \left(\frac{(1-\eta_s) P_{si} Q_{si}}{P_q M_{qsi}}\right)^{\lambda_{qs}}$, both relative to the industry average.

we next examine whether the conclusions about the GO–VA discrepancy survive alternative calibrations. Calibrating output elasticities to US input shares implicitly treats the US economy as undistorted at the sector level (Hsieh and Klenow, 2009). The identification assumption may fail because between-sector distortions exist even in the US economy. Furthermore, US output elasticities might be different from those of China and India because production technologies differ across countries.[21] To examine the robustness of our results, we therefore report results using two alternative calibration strategies: calibrating to country-specific input shares, and estimating the production function parameters using the Levinsohn-Petrin method. Table 2 reports a summary of the results, with detailed annual estimates reported in Online Appendix B.2.

The levels of the estimated efficiency gains vary substantially across calibrations, in particular for China. The conclusions relevant to our exercise are more stable. Unlike from the baseline, the alternative calibrations produce a negative aggregate VA bias in both countries. But at the sector level, we consistently find observations with a positive bias. Moreover, China consistently has smaller absolute VA bias both in levels and in logs across

[21] This consideration leads the recent study of Bils et al. (2021) to use country-specific input shares.

calibrations.

The sensitivity of the gain levels mainly reflects the large difference in the intermediate input shares between China and the US. The average is 0.75 for China and 0.49 for the US.[22] A higher output elasticity of intermediate inputs translates into a larger network propagation effect. But through the theoretical mapping, it results in a smaller VA elasticity of substitution. This explains why the VA gains are much smaller when the output elasticities are calibrated to or estimated with Chinese data. The average share is 0.43 in India, much closer to that in the US. The TFP gains for India thus change by a smaller magnitude under alternative calibration strategies. In the last two rows of Table 2, we further confirm the importance of the intermediate input shares by presenting results calibrating to country-specific capital and labor shares and US intermediate input shares. The difference from the baseline results is substantially narrowed. This sensitivity does not overturn the two conclusions emphasized above, but it cautions against interpreting any one calibration as the true level of misallocation, given the difficulties in identifying the true production function parameters.

Table 2: The VA Bias across Different Parameterizations

Calibration	Country	GO	VA	Level gap	Log gap	% positive
U.S. Shares	China	1.607	1.665	0.058	0.021	49.1
	India	0.623	0.347	-0.276	-0.187	2.7
Country-specific Shares	China	0.635	0.574	-0.062	-0.039	15.1
	India	0.951	0.733	-0.218	-0.118	4.7
Levinsohn–Petrin	China	0.245	0.083	-0.162	-0.139	0.1
	India	0.597	0.365	-0.232	-0.157	2.9
Mixed Shares	China	1.611	1.676	0.065	0.024	49.2
	India	0.720	0.426	-0.293	-0.187	3.5

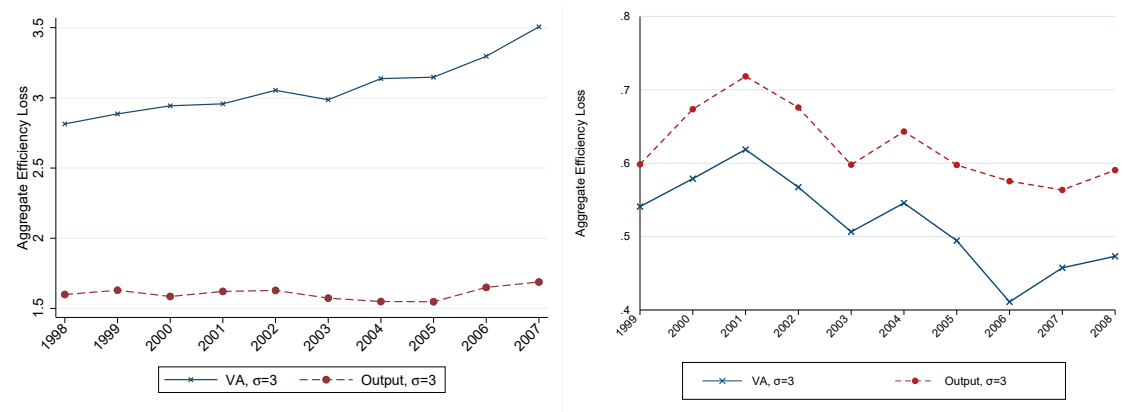
Note: Efficiency gains are measured as $\left(\frac{Y^E}{Y}\right)^o - 1$ and $\left(\frac{Y^E}{Y}\right)^{va} - 1$. The level gap is $\left(\frac{Y^E}{Y}\right)^{va} - \left(\frac{Y^E}{Y}\right)^o$. The log gap is the exact B in Proposition 4, approximated in Proposition 5. Mixed shares refer to using country-specific shares for capital and labor and US shares for intermediate inputs. The last column is the percentage of sector-year observations in which the VA bias is positive. All reported numbers are averaged over the sample period.

[22] Online Appendix B.2 presents density plots of the input shares for the countries.

Inconsistent Calibration of VA Parameters. So far, we have kept the choice of the elasticity of substitution and the sectoral weights under the VA approach consistent with the mapping in Proposition 2 across all calibration strategies. In practice, these parameters could be miscalibrated, which leads to further bias in the VA estimates.

As discussed in Section 3.1, the choice of the elasticity of substitution is probably most problematic. Because $\sigma_s > 1$ for gross output, the theory-consistent VA elasticity should be set at a value smaller than the GO elasticity. Yet the value-added studies have often chosen the elasticity based on estimates for gross output. This implies that the VA estimates tend to overstate the cost of misallocation by using a higher elasticity of substitution, as measured cost of misallocation rises with the elasticity. HK use 3 as a conservative value for the elasticity in their baseline calibration. If we take 3 as the elasticity for gross output, the theory-consistent choice for value added is actually 2 if $\eta_s = 0.5$.

Figure 5: The Impact of Inconsistent Elasticity of Substitution



(a) China (b) India

Note: Efficiency gains are measured as $\left(\frac{Y^E}{Y}\right)^{o} - 1$ and $\left(\frac{Y^E}{Y}\right)^{va} - 1$, with $\sigma = 3$ in both models.

Figure 5 evaluates the resulting bias by setting the elasticity to 3 in both models. In China, the average TFP gain measured under the VA approach becomes 147 percentage points larger than that under the GO approach over the sample years, compared to an average GO gain of 161%. In India, the difference between the two approaches is substantially

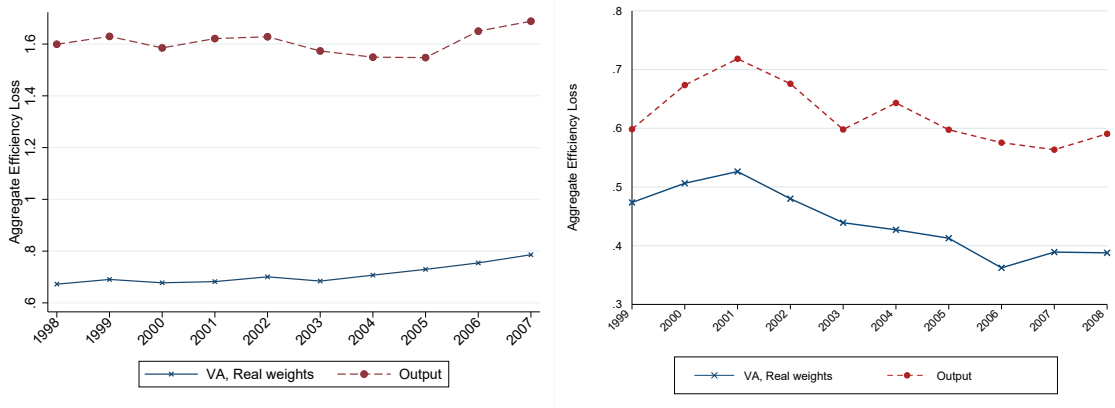
narrowed by over 17 percentage points, although the VA approach still underestimates the TFP gain. Thus, using the GO elasticity in the VA model creates a sizeable upward component in the VA estimate.[23] The very different results for China and India, however, show that it is unclear whether the bias would bring the VA estimates closer to or further away from the GO estimates.

A similar issue arises for sectoral weights. Proposition 2 maps GO influence weights into VA weights, whereas empirical VA applications commonly use sectoral value-added shares. The two coincide only under the additional restriction of no between-sector intermediate input distortions. Figure 6 presents the results from calibrating the VA weights under common practice. Panel (a) shows that the VA estimates for China are substantially lowered if the value-added shares are used as sectoral weights. This is because the intermediate input share of gross output is much higher in Chinese data than in US data, such that sectoral value-added shares are substantially lower than the theory-consistent weights. The opposite is true for India because its intermediate input shares are slightly lower than the US. The magnitude of the change in the VA estimates is smaller in India as the difference in intermediate input shares between India and US is smaller than that between China and India.

Consistent calibration of the VA weights also requires identification of the output elasticity of intermediate inputs. We use US input shares to calibrate the output elasticities mainly because the choice makes the potential problems in calibrating the weights transparent. If we instead calibrate the output elasticities to country-specific input shares, sectoral value-added shares coincide with the theory-consistent weights, such that this additional weight bias disappears. These exercises reinforce the distinction between our main focus in this paper, the bias from using a value-added approach, and the bias caused by inconsistent calibration. Although correct identification of the technology parameters from wedges is

[23]This conclusion does not rely on the elasticity being 3. The elasticity is smaller in the VA model for any value larger than 1. Thus, as long as we mistake the GO elasticity for the VA elasticity, there is an upward bias of the VA approach.

Figure 6: The Impact of Inconsistent Sectoral Weights



(a) China (b) India

Note: Efficiency gains are measured as $\left(\frac{Y^E}{Y}\right)^o - 1$ and $\left(\frac{Y^E}{Y}\right)^{va} - 1$. The VA sectoral weights are sectoral VA shares.

pivotal for the study of misallocation, this does not diminish the value of our discussion of the conceptual issues in using the value-added framework.

5 Conclusion

This paper studies how using a VA approach would bias the estimates of the cost of misallocation. The bias comes from two sources: incorrect aggregation in the VA model and incorrect inference of firm productivity and wedges using value-added data. The two approaches are equivalent when there are no within-sector intermediate input distortions. With such distortions, this equivalence fails, and the bias can be positive or negative. The widely used VA framework of HK therefore does not necessarily understate or overstate the cost of resource misallocation. We find both positive and negative biases in Chinese and Indian data. The absolute bias is much smaller in China than in India, which appears to be explained by its less dispersed intermediate input distortions.

The findings in this paper support the idea that a VA model is not inherently invalid. It can be a correct representation of the underlying data when there are no intermediate input distortions. However, the VA model can be easily misspecified if we fail to distinguish the

two perspectives explicitly, a point also emphasized in Herrendorf et al. (2013). The recent surge in the study of production networks provides many insights regarding the amplification of productivity shocks and market frictions through IO linkages. Our study shows that the measured aggregate effects of resource misallocation might be similar between a GO model with production networks and a VA model without, as the network amplification effect is already embedded in the value-added measures. The presence of intermediate input distortions, however, may bias the VA estimates in an unpredictable direction and with an unknown magnitude.

Finally, we would like to emphasize that the theoretical arguments in this paper are not confined to the HK accounting framework. Any studies of misallocation that rely on a VA framework could in theory be misspecified, and the inference of wedges could also be biased if it is based on value-added data. Our recommendation is to use the GO approach in studies of within-sector misallocation, which can often be implemented just as easily but does not suffer from the same conceptual bias as the VA approach.

Online Appendix

A. Proofs

Lemma 1 From the first-order conditions for profit maximization, we can relate variety price to firm's physical productivity and wedges,

$$P_{si} = \frac{\sigma}{\sigma-1}\frac{((1+\tau_{Ksi})R)^{\alpha_s\eta_s}((1+\tau_{Lsi})W)^{(1-\alpha_s)\eta_s}\left((1+\tau_{Msi})\prod_{q=1}^{S}P_q^{\lambda_{qs}}\right)^{1-\eta_s}}{A_{si}}.$$

Because the input prices are common across firms and the demand for a variety is isoelastic, it follows that,

$$P_{si}Q_{si} \propto \left(\frac{((1+\tau_{Ksi}))^{\alpha_s\eta_s}((1+\tau_{Lsi}))^{(1-\alpha_s)\eta_s}(1+\tau_{Msi})^{1-\eta_s}}{A_{si}}\right)^{1-\sigma}.$$

With Cobb-Douglas technology, a firm's input demand is proportional to its revenue. For example, the demand for capital is given by,

$$K_{si} = \frac{\sigma_s-1}{\sigma_s}\frac{\alpha_s\eta_s P_{si}Y_{si}}{(1+\tau_{Ksi})R} \propto \frac{1}{1+\tau_{Ksi}}\left(\frac{((1+\tau_{Ksi}))^{\alpha_s\eta_s}((1+\tau_{Lsi}))^{(1-\alpha_s)\eta_s}(1+\tau_{Ms})^{1-\eta_s}}{A_{si}}\right)^{1-\sigma}.$$

It then follows that each firm's input demand is proportional to sectoral input supply, with the proportionality determined by firm physical productivity and wedges. Substituting the input demand into the production function, it follows that the sectoral production function inherits the Cobb-Douglas form of the firm production function,

$$Q_s = TFP_s \cdot \left(K_s^{\alpha_s}L_s^{1-\alpha_s}\right)^{\eta_s}\left(\prod_{q=1}^{S}M_{qs}^{\lambda_{qs}}\right)^{1-\eta_s}.$$

We next derive TFP in the sectoral production function. Note that we define sectoral

revenue productivity as,

$$TFPR_s \equiv \frac{P_s Q_s}{(K_s^{\alpha_s} L_s^{1-\alpha_s})^{\eta_s} \left(\prod_{q=1}^{S} M_{qs}^{\lambda_{qs}}\right)^{1-\eta_s}},$$

Combining this definition with the production function, we have,

$$TFP_s \equiv \frac{Q_s}{(K_s^{\alpha_s} L_s^{1-\alpha_s})^{\eta_s} \left(\prod_{q=1}^{S} M_{qs}^{\lambda_{qs}}\right)^{1-\eta_s}} = \frac{TFPR_s}{P_s}.$$

Substituting the CES price aggregator P_s and using $P_{si} = \frac{TFPR_{si}}{A_{si}}$ yields Lemma 1. □

Proposition 1 With the Domar weights defined as $v_s = \frac{P_s Q_s}{Y}$, we can solve for the sectoral intermediate-input demand as,

$$M_{qs} = \frac{1}{\mathcal{T}_{Ms}} \lambda_{qs}(1-\eta_s)\frac{P_s Q_s}{P_q} = \frac{1}{\mathcal{T}_{Ms}} b_{qs}\frac{v_s}{v_q} Q_q.$$

Sectoral demand for capital and labor can be determined by

$$\begin{aligned}
\frac{K_s}{K} &= \frac{\frac{1}{\mathcal{T}_{Ks}}\alpha_s \eta_s v_s}{\sum_{q=1}^{S} \frac{1}{\mathcal{T}_{Kq}}\alpha_q \eta_q v_q} \equiv \beta_{Ks}, \\
\frac{L_s}{L} &= \frac{\frac{1}{\mathcal{T}_{Ls}}(1-\alpha_s)\eta_s v_s}{\sum_{q=1}^{S} \frac{1}{\mathcal{T}_{Lq}}(1-\alpha_q)\eta_q v_q} \equiv \beta_{Ls},
\end{aligned}$$

where $\mathcal{T}_{Ks} = \alpha_s \eta_s \frac{P_s Q_s}{R K_s}$ and $\mathcal{T}_{Ls} = (1-\alpha_s)\eta_s \frac{P_s Q_s}{W L_s}$ summarize the effects of distortions on sectoral capital and labor demand. Plugging these conditions into the sectoral production function, we obtain the sectoral production function,

$$Q_s = TFP_s \cdot \left((\beta_{Ks} K)^{\alpha_s} (\beta_{Ls} L)^{1-\alpha_s}\right)^{\eta_s} \left[\prod_{q=1}^{S} \left(\frac{1}{\mathcal{T}_{Ms}} b_{qs}\frac{v_s}{v_q} Q_q\right)^{\lambda_{qs}}\right]^{1-\eta_s}.$$

Taking logs of the sectoral production functions and stacking them in vector form,

$$\bar{q} = \bar{a} + \omega_q + \delta_K \log K + \delta_L \log L + B'\bar{q},$$

where $\bar{q}$ is a vector of $\log Q_s$, δ_K a vector of $\alpha_s\eta_s$, δ_L a vector of $(1-\alpha_s)\eta_s$, and ω_q is a vector of the allocation terms whose s^{th} element is given by $\alpha_s\eta_s \log \beta_{Ks} + (1-\alpha_s)\eta_s \log \beta_{Ls} + (1-\eta_s)\sum_{q=1}^{S} \lambda_{qs} \log\left(\frac{1}{\mathcal{T}_{Ms}} b_{qs} \frac{v_s}{v_q}\right)$. The vector of log output is solved as,

$$\bar{q} = (I - B')^{-1}(\bar{a} + \omega_q + \delta_K \log K + \delta_L \log L).$$

Notice that we can write $C_s = \frac{\theta_s Q_s}{v_s}$. Taking logs and stacking it into a vector, we have,

$$\bar{c} = \omega_c + \bar{q},$$

where $\bar{c}$ is the vector of $\log C_s$ and ω_c a vector of $\log \frac{\theta_s}{v_s}$. Using the final good production function, we have,

$$\log Y = \theta'\bar{c} = \theta'[\omega_c + (I - B')^{-1}(\bar{a} + \omega_q + \delta_K \log K + \delta_L \log L)],$$

where θ is the vector of sectoral weights in final consumption. This equation then leads to a Cobb-Douglas aggregate production function with the output elasticities of capital and labor given by $\theta'(I-B')^{-1}\delta_K$ and $\theta'(I-B')^{-1}\delta_L$. Since $\delta_K+\delta_L$ can be computed as $(I-B')\mathbf{1}$ where $\mathbf{1}$ is the vector of ones, it follows that $\theta'(I - B')^{-1}(\delta_K + \delta_L) = 1$, such that the aggregate production function has constant returns to scale. □

Proposition 2 We configure the VA parameters in a step-by-step procedure. First note that equating the allocation of capital within a sector in the two models requires the

following condition,

$$\frac{\frac{P_{Ysi}Y_{si}}{1+\tau_{Ksi}}}{\sum_{i=1}^{N_s}\frac{P_{Ysi}Y_{si}}{1+\tau_{Ksi}}} = \frac{K_{si}}{K_s} = \frac{\frac{P_{si}Q_{si}}{1+\tau_{Ksi}}}{\sum_{i=1}^{N_s}\frac{P_{si}Q_{si}}{1+\tau_{Ksi}}}.$$

This condition holds only if $P_{Ysi}Y_{si} \propto P_{si}Q_{si}$. The definition of firm value added and the first-order optimality condition for intermediate-input use imply,

$$P_{Ysi}Y_{si} = \left(1 - \frac{\sigma_s - 1}{\sigma_s}\frac{1-\eta_s}{1+\tau_{Msi}}\right) P_{si}Q_{si}.$$

Firm value added will be proportional to firm output only if all firms within a sector face the same distortion τ_{Msi}. It can be shown that if all firms face the same τ_{Msi}, allocation of labor is also the same in the two models. TFPRs in the two models are linked as,

$$\left(\frac{TFPR_s}{TFPR_{si}}\right)^{\frac{1}{\eta_s}} \propto \frac{\widehat{TFPR}_s}{\widehat{TFPR}_{si}}.$$

From the pricing rule of firm products, we can relate firm's nominal output to productivity and inputs in the two models as follows,

$$\begin{aligned} P_{si}Q_{si} &\propto \left(A_{si}\left(K_{si}^{\alpha_s}L_{si}^{1-\alpha_s}\right)^{\eta_s}\left(\prod_{q=1}^{S}M_{qsi}^{\lambda_{qs}}\right)^{1-\eta_s}\right)^{\frac{\sigma_s-1}{\sigma_s}}, \\ P_{Ysi}Y_{si} &\propto \left(\widehat{A}_{si}K_{si}^{\widehat{\alpha}_s}L_{si}^{1-\widehat{\alpha}_s}\right)^{\frac{\widehat{\sigma}_s-1}{\widehat{\sigma}_s}}, \end{aligned}$$

where the term in the brackets on the right hand side is the firm-level production function in the respective model. We have established that firm value added should be proportional to gross output. Combined with the above conditions we can reach a proportional relationship between firm production in the two models. Intermediate inputs show up in the production of gross output but not value added. We replace intermediate inputs using the optimality condition for intermediate-input use. For the VA model to be consistent with data, the

following conditions must hold,

$$\left(A_{si}^{\frac{1}{\eta_s}} K_{si}^{\alpha_s} L_{si}^{1-\alpha_s}\right)^{\frac{(\sigma_s-1)\eta_s}{\sigma_s\eta_s+(1-\eta_s)}} \propto \left(\widehat{A}_{si} K_{si}^{\widehat{\alpha}_s} L_{si}^{1-\widehat{\alpha}_s}\right)^{\frac{\widehat{\sigma}_s-1}{\widehat{\sigma}_s}}.$$

From this condition, we establish that $\widehat{\alpha}_s = \alpha_s$ and $\widehat{\sigma}_s = 1 + \eta_s(\sigma_s - 1)$. Firm value-added productivity satisfies the condition, $\widehat{A}_{si} \propto A_{si}^{\frac{1}{\eta_s}}$. The above conditions guarantee within-sector allocation of primary inputs is the same in the two models.

Under the specification of firm productivity, output elasticities and the elasticity of substitution, we can show that sectoral TFP gains in the two models satisfy,

$$\frac{\widehat{TFP}_s^E}{\widehat{TFP}_s} = \left(\frac{TFP_s^E}{TFP_s}\right)^{\frac{1}{\eta_s}}.$$

To make sure aggregate gains are the same in the two models, sectoral weights in the VA model must be proportional to those in the GO model by a factor of η_s, $\widehat{\theta}_s = \eta_s \tilde{v}_s$.

Proof of necessity of Assumption 1 requires one fixed VA parameterization to reproduce the GO primary-input allocations for every admissible firm configuration and wedges. Comparing the two capital-share formulas shows that the intermediate wedge must be common. This is necessity for a universal representation. A single realized gain may coincide accidentally under heterogeneous wedges. □

Proposition 4 For the GO approach, firm productivity and wedges are correctly inferred, so the efficient sectoral TFP is given as in the text, $TFP^E = \left(\sum_{i=1}^N A_i^{\sigma-1}\right)^{\frac{1}{\sigma-1}}$. We have shown above that firm revenue is proportional to a combination of firm productivity and wedges,

$$P_i Q_i \propto \left(\frac{((1+\tau_{Li}))^{\eta}(1+\tau_{Mi})^{1-\eta}}{A_i}\right)^{1-\sigma}.$$

Let the term in the brackets be $r_i = \frac{A_i^{\sigma-1}}{((1+\tau_{Li}))^{\eta(\sigma-1)}(1+\tau_{Mi})^{(1-\eta)(\sigma-1)}}$. HK show that sectoral MRP is a harmonic mean of firm MRPs weighted by each firm's revenue share. The MRPs

can thus be written as,

$$MRPL \propto \frac{1}{\sum_{i=1}^{N} \frac{1}{1+\tau_{Li}} \frac{r_i}{\sum_{i=1}^{N} r_i}}, \text{ and } MRPM \propto \frac{1}{\sum_{i=1}^{N} \frac{1}{1+\tau_{Mi}} \frac{r_i}{\sum_{i=1}^{N} r_i}},$$

where the proportional factor will cancel out in the computation of the efficiency gain. It then follows that TFPR can be given by,

$$TFPR \propto \left(\frac{1}{\sum_{i=1}^{N} \frac{1}{1+\tau_{Li}} \frac{r_i}{\sum_{i=1}^{N} r_i}} \right)^{\eta} \left(\frac{1}{\sum_{i=1}^{N} \frac{1}{1+\tau_{Mi}} \frac{r_i}{\sum_{i=1}^{N} r_i}} \right)^{1-\eta}.$$

Sectoral TFP can be then given as,

$$TFP = \frac{(\sum_{i=1}^{N} r_i)^{\frac{\sigma}{\sigma-1}}}{\left(\sum_{i=1}^{N} \frac{r_i}{1+\tau_{Li}}\right)^{\eta} \left(\sum_{i=1}^{N} \frac{r_i}{1+\tau_{Mi}}\right)^{1-\eta}}.$$

With a single sector, aggregate TFP is simply sectoral TFP to the power of $\frac{1}{\eta}$. Measured TFP gain in logs as given in the text then follows.

For the VA approach, we can derive the log of measured TFP gain similarly if firm value-added productivity and wedges are given,

$$L_{VA} = \frac{1}{\hat{\sigma}-1} \log \sum_{i=1}^{N} \hat{A}_i^{\hat{\sigma}-1} - \frac{\hat{\sigma}}{\hat{\sigma}-1} \log \sum_{i=1}^{N} \hat{r}_i + \log \sum_{i=1}^{N} \frac{\hat{r}_i}{1+\hat{\tau}_{Li}},$$

where $\hat{r}_i = \frac{\hat{A}_i^{\hat{\sigma}-1}}{(1+\hat{\tau}_{Li})^{\hat{\sigma}-1}}$.

Proposition 5 The bias from Proposition 4 can be rewritten as,

$$\begin{aligned} B =& \frac{1}{\eta(\sigma-1)} \log \sum_{i=1}^{N} \omega_i d_i^{1+\eta(\sigma-1)} (1+\tau_{Mi})^{(\eta-1)(\sigma-1)} + \frac{\sigma}{\eta(\sigma-1)} \log \sum_{i=1}^{N} \phi_i (1+\tau_{Mi})^{-(1-\eta)(\sigma-1)} \\ & - \frac{1-\eta}{\eta} \log \sum_{i=1}^{N} \phi_i (1+\tau_{Mi})^{-(1-\eta)(\sigma-1)-1} - \frac{1+\eta(\sigma-1)}{\eta(\sigma-1)} \log \sum_{i=1}^{N} \phi_i (1+\tau_{Mi})^{-(1-\eta)(\sigma-1)} d_i, \end{aligned}$$

where $\omega_i = \frac{A_i^{\sigma-1}}{\sum_{i=1}^N A_i^{\sigma-1}}$ and $\phi_i = \frac{\frac{A_i^{\sigma-1}}{((1+\tau_{Li}))^{\eta(\sigma-1)}}}{\sum_{i=1}^N \frac{A_i^{\sigma-1}}{((1+\tau_{Li}))^{\eta(\sigma-1)}}}$ are weights that only depend on productivity and the primary wedge. We can write it in a compact form as,

$$\begin{aligned} B =& \frac{1}{\eta(\sigma-1)} \underbrace{\log E_\omega d_i^{1+\eta(\sigma-1)} (1+\tau_{Mi})^{(\eta-1)(\sigma-1)}}_{T_1} + \frac{\sigma}{\eta(\sigma-1)} \underbrace{\log E_\phi (1+\tau_{Mi})^{-(1-\eta)(\sigma-1)}}_{T_2} \\ & - \frac{1-\eta}{\eta} \underbrace{\log E_\phi (1+\tau_{Mi})^{-(1-\eta)(\sigma-1)-1}}_{T_3} - \frac{1+\eta(\sigma-1)}{\eta(\sigma-1)} \underbrace{\log E_\phi (1+\tau_{Mi})^{-(1-\eta)(\sigma-1)} d_i}_{T_4}, \end{aligned}$$

where $E_\omega x$ indicates the expectation of x weighted by ω.

We then plug the transformation of $1+\tau_{Mi}$ and the second-order approximation of d_i into the Ts.

$$\begin{aligned} T_1 =& \log E_\omega \exp\left[-\frac{(\sigma-1)(1-\eta)\sigma}{2(1+\eta(\sigma-1))} \epsilon^2 z_i^2 + O(\epsilon^3) \right] \\ =& \log E_\omega \left[1 - \frac{(\sigma-1)(1-\eta)\sigma}{2(1+\eta(\sigma-1))} \epsilon^2 z_i^2 + O(\epsilon^3) \right] \\ =& \log \left[1 - \frac{(\sigma-1)(1-\eta)\sigma}{2(1+\eta(\sigma-1))} \epsilon^2 E_\omega z_i^2 + O(\epsilon^3) \right] \\ =& - \frac{(\sigma-1)(1-\eta)\sigma}{2(1+\eta(\sigma-1))} \epsilon^2 E_\omega z_i^2 + O(\epsilon^3), \end{aligned}$$

where the first equality plugs the transformation of $1+\tau_{Mi}$ and the approximation of d_i, the second equality applies a second-order expansion to the exponential function, the third equality uses the property of expectation, and the fourth equality applies a second-order expansion to the log function. The second and third Ts have similar structure.

$$\begin{aligned} T_j =& \log E_\phi \exp[b_j \epsilon z_i] \\ =& \log E_\phi \left[1 + b_j \epsilon z_i + \frac{b_j^2}{2} \epsilon^2 z_i^2 + O(\epsilon^3) \right] \\ =& \log \left[1 + b_j \epsilon E_\phi z_i + \frac{b_j^2}{2} \epsilon^2 E_\phi z_i^2 + O(\epsilon^3) \right] \\ =& b_j \epsilon E_\phi z_i + \frac{b_j^2}{2} \epsilon^2 E_\phi z_i^2 - \frac{b_j^2}{2} \epsilon^2 (E_\phi z_i)^2 + O(\epsilon^3), \forall j = 2, 3. \end{aligned}$$

where $b_2 = -(1-\eta)(\sigma-1)$, and $b_3 = -(1-\eta)(\sigma-1) - 1$.

$$\begin{aligned} T_4 &= \log E_\phi \exp\left[-b\epsilon z_i - c\epsilon^2 z_i^2\right] \\ &= \log E_\phi \left[1 - b\epsilon z_i + \frac{b^2 - 2c}{2}\epsilon^2 z_i^2 + O(\epsilon^3)\right] \\ &= \log \left[1 - b\epsilon E_\phi z_i + \frac{b^2 - 2c}{2}\epsilon^2 E_\phi z_i^2 + O(\epsilon^3)\right] \\ &= -b\epsilon E_\phi z_i + \left(\frac{b^2}{2} - c\right)\epsilon^2 E_\phi z_i^2 - \frac{b^2}{2}\epsilon^2 (E_\phi z_i)^2 + O(\epsilon^3). \end{aligned}$$

where $b = \frac{\eta(1-\eta)(\sigma-1)^2}{1+\eta(\sigma-1)}$ and $c = \frac{(\sigma-1)(1-\eta)\sigma}{2(1+\eta(\sigma-1))^2}$. Plugging the Ts into the formula for the bias and collecting terms, all first-order terms cancel out and the result in Proposition 5 follows. □

Corollary 2 We can rewrite the exact second-order approximation of the bias as,

$$B \approx \kappa[(E_\phi \log(1+\tau_{Mi}))^2 - E_\omega(\log(1+\tau_{Mi}))^2].$$

We then solve the two terms in the brackets respectively.

To solve the firm term, we first introduce a function $G_\phi(s)$,

$$G_\phi(s) = E_\phi(1+\tau_{Mi})^s.$$

Since $G'_\phi(0) = E_\phi \log(1+\tau_{Mi})$, we just have to solve $G_\phi(s)$ and take the first derivative at $s = 0$. We can expand $G_\phi(s)$ as,

$$G_\phi(s) = \frac{\sum_{i=1}^N A_i^{\sigma-1}(1+\tau_{Li})^{-\eta(\sigma-1)}(1+\tau_{Mi})^s}{\sum_{i=1}^N A_i^{\sigma-1}(1+\tau_{Li})^{-\eta(\sigma-1)}} = \frac{\frac{1}{N}\sum_{i=1}^N A_i^{\sigma-1}(1+\tau_{Li})^{-\eta(\sigma-1)}(1+\tau_{Mi})^s}{\frac{1}{N}\sum_{i=1}^N A_i^{\sigma-1}(1+\tau_{Li})^{-\eta(\sigma-1)}}$$

The numerator is the expectation of a log-normal distribution with mean $(\sigma-1)\mu_a$ and variance $(\sigma-1)^2\sigma_a^2 + \eta^2(\sigma-1)^2\sigma_l^2 + s^2\sigma_m^2 - 2\eta(\sigma-1)^2\sigma_{al} + 2s(\sigma-1)\sigma_{am} - 2\eta s(\sigma-1)\sigma_{lm}$. The denominator is also the expectation of a log-normal distribution with mean $(\sigma-1)\mu_a$ and variance $(\sigma-1)^2\sigma_a^2 + \eta^2(\sigma-1)^2\sigma_l^2 2\eta(\sigma-1)^2\sigma_{al}$. For a log-normal distribution X, we

have,

$$EX = \exp\left(E\log X + \frac{1}{2}Var(\log X)\right).$$

It then follows,

$$G_\phi(s) = \exp\left(\frac{1}{2}s^2\sigma_m^2 + s(\sigma-1)(\sigma_{am} - \eta\sigma_{lm})\right)$$

and

$$E_\phi \log(1+\tau_{Mi}) = G'_\phi(0) = (\sigma-1)(\sigma_{am} - \eta\sigma_{lm}).$$

To solve the second term, we similarly define,

$$G_\omega(s) = E_\omega(1+\tau_{Mi})^s,$$

as $G''_\omega(0) = E_\omega(\log(1+\tau_{Mi})^2)$. We then expand $G_\omega(s)$ as,

$$G_\omega(s) = \frac{\sum_{i=1}^N A_i^{\sigma-1}(1+\tau_{Mi})^s}{\sum_{i=1}^N A_i^{\sigma-1}} = \frac{\frac{1}{N}\sum_{i=1}^N A_i^{\sigma-1}(1+\tau_{Mi})^s}{\frac{1}{N}\sum_{i=1}^N A_i^{\sigma-1}}$$

The numerator is the expectation of a log-normal distribution with mean $(\sigma-1)\mu_a$ and variance $(\sigma-1)^2\sigma_a^2 + s^2\sigma_m^2 + 2s(\sigma-1)\sigma_{am}$. The denominator is also the expectation of a log-normal distribution with mean $(\sigma-1)\mu_a$ and variance $(\sigma-1)^2\sigma_a^2$. Using the property of log-normal distributions, it then follows,

$$G_\omega(s) = \exp\left(\frac{1}{2}s^2\sigma_m^2 + s(\sigma-1)\sigma_{am}\right)$$

and

$$E_\omega(\log(1+\tau_{Mi})^2) = G''_\omega(0) = \sigma_m^2 + (\sigma-1)^2\sigma_{am}^2.$$

Collecting terms then leads to the results in Corollary 2. □

B. Empirical Appendix

B.1 Data Preparation

Following statistical procedures of the Chinese National Bureau of Statistics (2007, 2008), we construct gross output as total industrial output plus value-added tax. When reported value-added tax is negative, we assume the tax is zero. Intermediate input is constructed as total intermediate-input expenditure minus interest payment. Value added is then constructed as gross output minus intermediate input. Capital stock is defined as the book value of fixed capital net of depreciation. Wage bill includes wages, retirement and unemployment insurance, health insurance, housing benefits, and employee supplementary benefits. Labor compensation in the data is systematically under-reported such that aggregate labor share in the data is much smaller than that in the national accounts.[24] To correct for the under-reporting, we adjust the wage bill to make aggregate labor share in the data consistent with national accounts data.

We clean the Chinese data as follows. We first drop all observations with key variables missing or having non-positive values. We drop inconsistent observations with value added lower than the wage bill. We also drop firms with fewer than 8 workers, as firms with fewer than 8 employees are not classified as private firms but as self-employed enterprises. Following HK, we first trim the 1% tails of average products in each year, relative to the industry mean. At this stage we compute industry input shares. The intermediate shares are those presented in Figure 1. We then merge the trimmed data with U.S. factor shares. Observations from industries that do not have a U.S. counterpart are dropped at this stage. To construct the efficiency gain measures, we further trim the 1% tails of TFPR and TFPQ using the calibrated production function parameters. Sectoral weights are constructed at this stage. Table B1 reports the number of plants before and after data cleaning for each year. For the years that are also studied by HK, the resulting sample size is comparable

[24] It can be clearly seen in the data. For example, 59% of firms report zero unemployment insurance payment, 38% of firms report zero health insurance payment, while both are mandatory by law.

between the two studies.

In the Indian data, value added is constructed as gross output minus intermediate input. Capital is measured as the average of the net book value of fixed capital at the beginning and end of a fiscal year. The measure of labor compensation is the sum of wages, bonuses, and benefits, which we use as our measure of labor input. We use a similar procedure to clean the Indian data. We first drop all observations with key variables missing, having non-positive values, or having value added smaller than the wage bill. We trim the data and construct input shares using the same procedure as above. Table B1 also reports the sample size in each year for India. Nearly 40% of the observations in India are dropped, mainly because value added turns out to be smaller than the wage bill.

Table B1: Number of Plants

China			India		
Year	Before	After	Year	Before	After
1998	165,118	98,100	1999	25,332	10,363
1999	162,033	105,491	2000	33,515	11,777
2000	162,883	102,820	2001	41,096	15,034
2001	171,240	116,405	2002	42,242	16,544
2002	181,557	126,417	2003	41,846	17,033
2003	196,222	141,930	2004	56,889	22,869
2004	274,763	197,853	2005	49,340	19,807
2005	271,835	200,742	2006	57,304	21,860
2006	301,961	225,552	2007	66,875	22,342
2007	336,768	255,756	2008	56,888	20,005

Notes: This table reports the number of plants before and after data cleaning for each country and year.

Tables B2 and B3 report the dispersion of TFPQ and TFPR by year for China and India, respectively. GO TFPQ is less dispersed than VA TFPQ in both China and India, which confirms the finding of Gandhi et al. (2017). GO TFPR is also less dispersed than VA TFPR in both countries. The gap, however, is larger in China than in India, consistent with the finding that MRPM is less dispersed in China.

Table B2: Dispersion of TFPQ and TFPR: China

	TFPQ						TFPR					
	Output			Value Added			Output			Value Added		
Year	S.D.	90-10	75-25	S.D.	90-10	75-25	S.D.	90-10	75-25	S.D.	90-10	75-25
1998	0.715	1.850	0.993	1.511	3.949	2.103	0.357	0.929	0.490	0.715	1.864	0.979
1999	0.726	1.888	1.018	1.547	4.059	2.168	0.357	0.936	0.496	0.721	1.888	1.004
2000	0.731	1.903	1.035	1.566	4.112	2.220	0.350	0.917	0.483	0.714	1.865	0.986
2001	0.723	1.897	1.033	1.558	4.102	2.223	0.347	0.908	0.481	0.710	1.860	0.989
2002	0.731	1.927	1.048	1.580	4.164	2.261	0.348	0.910	0.481	0.716	1.864	0.984
2003	0.729	1.928	1.058	1.569	4.148	2.281	0.339	0.889	0.467	0.703	1.840	0.969
2004	0.695	1.833	1.014	1.539	4.042	2.188	0.325	0.852	0.450	0.689	1.797	0.948
2005	0.715	1.897	1.028	1.580	4.179	2.267	0.328	0.860	0.458	0.697	1.824	0.966
2006	0.730	1.944	1.062	1.598	4.260	2.295	0.335	0.884	0.467	0.707	1.855	0.986
2007	0.745	1.980	1.094	1.628	4.344	2.350	0.338	0.886	0.473	0.717	1.875	1.014

Notes: TFPR is defined as $\frac{P_{si}Q_{si}}{\left(K_{si}^{\alpha_s}L_{si}^{1-\alpha_s}\right)^{\eta_s}\left(\prod_{q=1}^{S}M_{qsi}^{\lambda_{qs}}\right)^{1-\eta_s}}$ and $\frac{P_{Ysi}Y_{si}}{K_{si}^{\alpha_s}L_{si}^{1-\alpha_s}}$ for the GO and VA model respectively. TFPQ is defined as $\frac{Q_{si}}{\left(K_{si}^{\alpha_s}L_{si}^{1-\alpha_s}\right)^{\eta_s}\left(\prod_{q=1}^{S}M_{qsi}^{\lambda_{qs}}\right)^{1-\eta_s}}$ and $\frac{Y_{si}}{K_{si}^{\alpha_s}L_{si}^{1-\alpha_s}}$ for the GO and the VA model respectively. Reported statistics are computed for the log of firm values relative to industry mean. S.D. is standard deviation. 90-10 is the difference between 90th and 10th percentile, and 75-25 is that between 75th and 25th percentile. Statistics are computed for each industry and then summed up weighted by industry output shares and value-added shares.

Table B3: Dispersion of TFPQ and TFPR: India

	TFPQ						TFPR					
	Output			Value Added			Output			Value Added		
Year	S.D.	90-10	75-25	S.D.	90-10	75-25	S.D.	90-10	75-25	S.D.	90-10	75-25
1999	1.077	2.869	1.603	2.516	6.724	3.802	0.339	0.864	0.455	0.627	1.609	0.883
2000	1.096	2.906	1.694	2.543	6.766	4.045	0.347	0.889	0.458	0.626	1.616	0.849
2001	1.037	2.728	1.564	2.361	6.238	3.633	0.344	0.869	0.462	0.623	1.605	0.842
2002	0.981	2.610	1.435	2.299	6.136	3.624	0.360	0.921	0.485	0.629	1.622	0.835
2003	1.002	2.607	1.550	2.405	6.251	3.898	0.333	0.839	0.436	0.586	1.511	0.807
2004	1.026	2.737	1.377	2.446	6.537	3.055	0.356	0.896	0.470	0.602	1.552	0.832
2005	1.024	2.700	1.531	2.578	6.549	4.034	0.337	0.848	0.456	0.595	1.465	0.796
2006	1.063	2.706	1.646	2.762	6.885	4.603	0.340	0.905	0.475	0.603	1.393	0.716
2007	1.011	2.682	1.546	2.619	6.476	4.373	0.346	0.863	0.457	0.592	1.430	0.791
2008	1.068	2.834	1.651	2.771	7.002	4.529	0.360	0.972	0.450	0.621	1.691	0.741

Notes: TFPR is defined as $\frac{P_{si}Q_{si}}{\left(K_{si}^{\alpha_s}L_{si}^{1-\alpha_s}\right)^{\eta_s}\left(\prod_{q=1}^{S}M_{qsi}^{\lambda_{qs}}\right)^{1-\eta_s}}$ and $\frac{P_{Ysi}Y_{si}}{K_{si}^{\alpha_s}L_{si}^{1-\alpha_s}}$ for the GO and VA model respectively. TFPQ is defined as $\frac{Q_{si}}{\left(K_{si}^{\alpha_s}L_{si}^{1-\alpha_s}\right)^{\eta_s}\left(\prod_{q=1}^{S}M_{qsi}^{\lambda_{qs}}\right)^{1-\eta_s}}$ and $\frac{Y_{si}}{K_{si}^{\alpha_s}L_{si}^{1-\alpha_s}}$ for the GO and the VA model respectively. Reported statistics are computed for the log of firm values relative to industry mean. S.D. is standard deviation. 90-10 is the difference between 90th and 10th percentile, and 75-25 is that between 75th and 25th percentile. Statistics are computed for each industry and then summed up weighted by industry output shares and value-added shares.

B.2 Additional Empirical Results

This section reports additional empirical results. Table B4 reports the aggregate TFP gains for each country and year, and the variance of intermediate-input distortions and its covariance with primary-input distortions. Table B5 further reports the variance-covariance matrix for primary and intermediate-input distortions. The numbers reported in this table

are cited in Section 4.2 in the paper.

Table B4: Aggregate TFP Gain

China					India				
Year	GO	VA	Var(τ_M)	Cov(τ_M,τ_Y)	Year	GO	VA	Var(τ_M)	Cov(τ_M,τ_Y)
1998	159.9	151.5	0.051	-0.052	1999	59.8	47.4	0.266	-0.112
1999	163.0	156.2	0.043	-0.046	2000	67.4	50.6	0.310	-0.151
2000	158.5	158.3	0.037	-0.038	2001	71.8	52.6	0.298	-0.136
2001	162.1	159.2	0.033	-0.037	2002	67.6	48.0	0.315	-0.128
2002	162.8	163.2	0.033	-0.032	2003	59.8	43.9	0.274	-0.111
2003	157.3	162.7	0.029	-0.027	2004	64.3	42.7	0.308	-0.115
2004	154.9	171.3	0.040	-0.030	2005	59.8	41.3	0.261	-0.109
2005	154.8	172.6	0.033	-0.026	2006	57.5	36.2	0.234	-0.075
2006	165.0	180.1	0.033	-0.026	2007	56.4	38.9	0.265	-0.097
2007	168.8	190.0	0.037	-0.026	2008	59.1	38.8	0.345	-0.169

Note: GO and VA indicate aggregate TFP gains computed as $100 \times \left(\frac{Y^E}{Y}\right)^o - 100$ and $100 \times \left(\frac{Y^E}{Y}\right)^{va} - 100$. Var($\tau_M$) is the variance of the marginal revenue products of intermediate inputs (in logs relative to industry mean). Cov(τ_M,τ_Y) is the covariance between the marginal revenue products of intermediate inputs and primary inputs (in logs relative to industry mean). The two statistics are averaged over industries with industry output share as weights.

Table B5: Variance-Covariance Matrix of Marginal Revenue Products

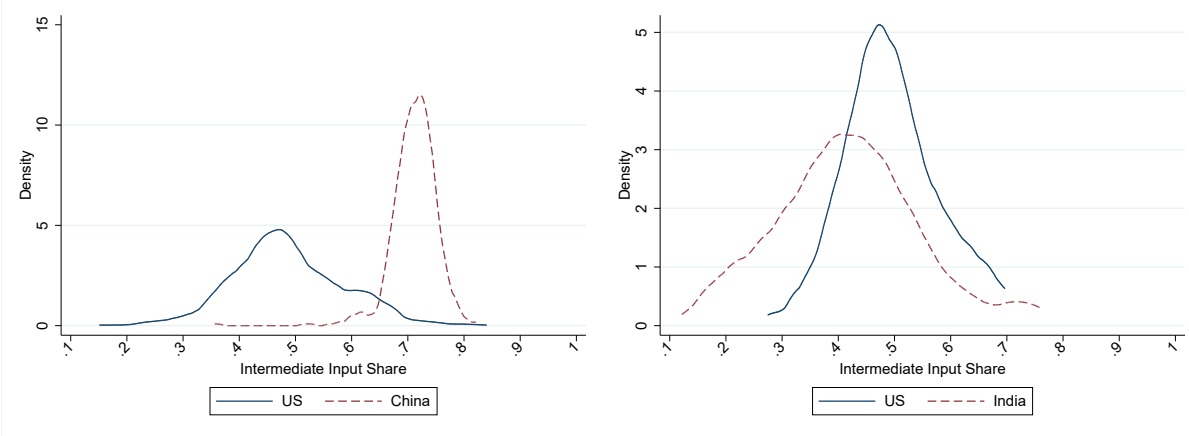
	China		India	
	Primary	Intermediate	Primary	Intermediate
Primary	0.522		0.454	
Intermediate	-0.034	0.037	-0.120	0.288

Note: Marginal revenue products are measured as $MRPK_{si}^{\alpha_s} MRPL_{si}^{1-\alpha_s}$ and $\prod_{q=1}^{S} MRPM_{qsi}^{\lambda_{qs}}$ (in logs), both relative to the industry average.

Figure B1 presents the kernel densities of industry intermediate-input shares in China and India, respectively, in comparison with the U.S. benchmark. China has much larger and more compressed intermediate-input shares, while the Indian intermediate-input shares are only slightly smaller but more dispersed than their U.S. counterparts. These differences are the key drivers of the drastic changes in the estimated cost of misallocation under different calibration strategies.

Figures B2, B3, and B4 report aggregate TFP gains under three alternative calibration

Figure B1: Intermediate-Input Shares



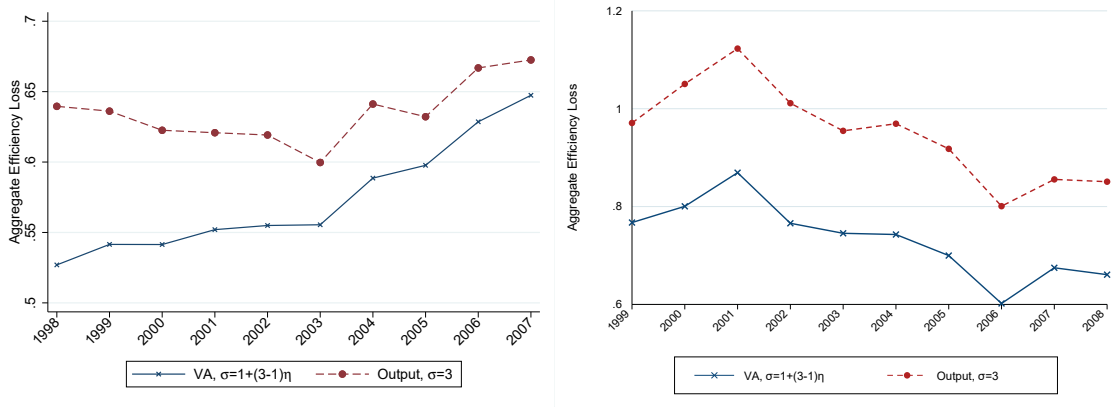
(a) China (b) India

Note: Kernel densities of industry intermediate-input shares averaged over the sample years are plotted for China and India against those of the U.S. The comparisons are made separately because of differences in the industry classification systems used in China and India.

strategies reported in the main text. The first calibrates the production function parameters to country-specific input shares. The second uses production function parameters estimated with a Levinsohn-Petrin method.[25] The third uses country-specific capital and labor shares and U.S. intermediate-input shares. In all cases, the value-added elasticity of substitution and sectoral weights are calibrated in a theory-consistent way.

[25]We could not report results using the well-known Olley-Pakes production function estimates because we do not have information on investment in the Indian data.

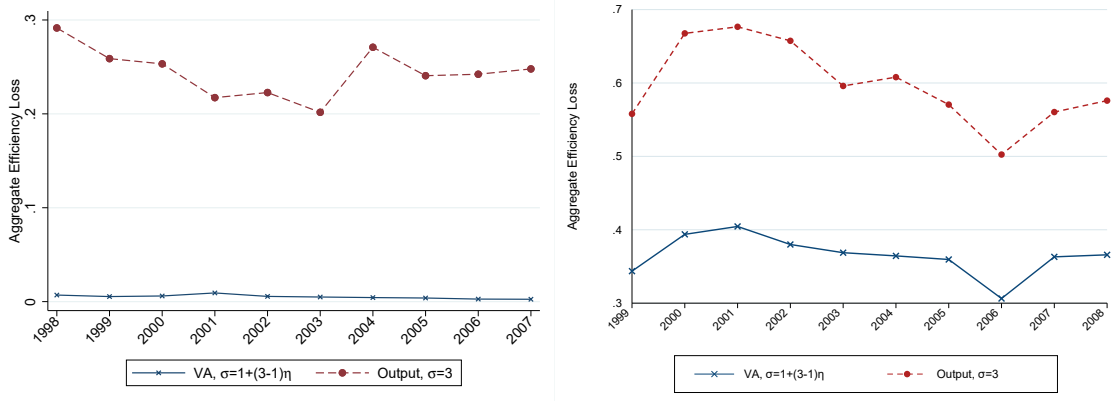
Figure B2: Aggregate TFP Gains: Country-Specific Input Shares



(a) China (b) India

Note: Efficiency gains are measured as $\left(\frac{Y^E}{Y}\right)^o - 1$ and $\left(\frac{Y^E}{Y}\right)^{va} - 1$. The output elasticities are calibrated to country-specific input shares.

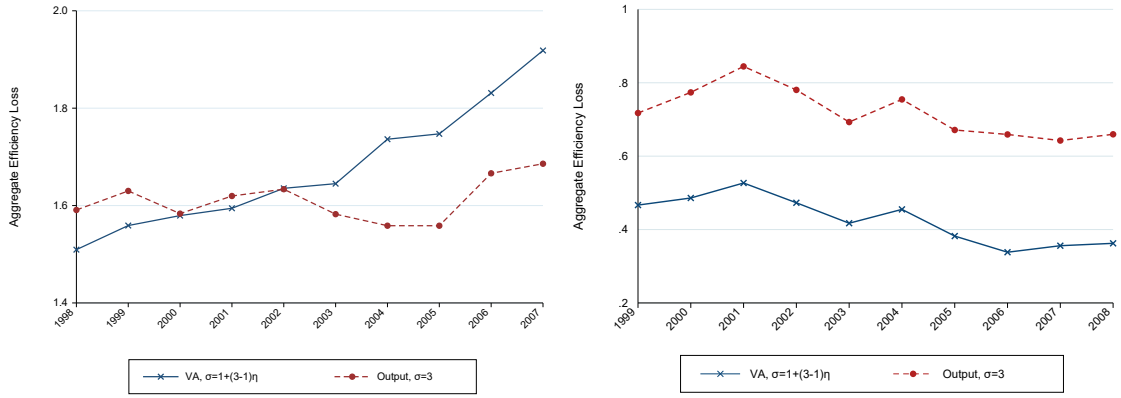
Figure B3: Aggregate TFP Gains: Production Function Estimates Using Levinsohn-Petrin



(a) China (b) India

Note: Aggregate TFP gain is defined as $\left(\frac{Y^E}{Y}\right)^o - 1$ and $\left(\frac{Y^E}{Y}\right)^{va} - 1$. The output elasticities are estimated using the Levinsohn-Petrin method.

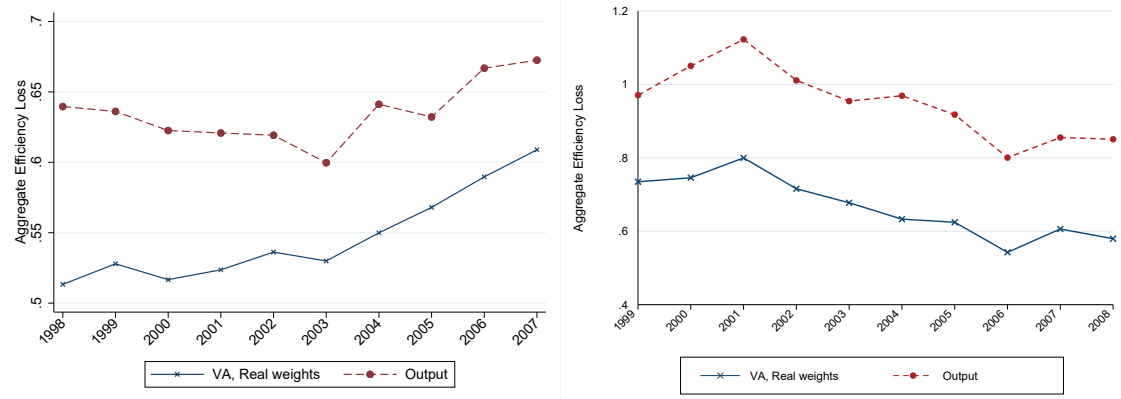
Figure B4: Aggregate TFP Gains: Country-Specific Primary-Input Shares and U.S. Intermediate-Input Shares



(a) China (b) India

Note: Aggregate TFP gain is defined as $\left(\frac{Y^E}{Y}\right)^{o} - 1$ and $\left(\frac{Y^E}{Y}\right)^{va} - 1$. The capital and labor shares within primary inputs are calibrated to country-specific shares, while the output elasticity of intermediate inputs is calibrated to U.S. shares. The VA elasticity and sectoral weights are mapped consistently from the corresponding GO calibration.

Figure B5: Aggregate TFP Gains: Country-Specific Input Shares and Actual VA Weights



(a) China (b) India

Note: Aggregate TFP gain is defined as $\left(\frac{Y^E}{Y}\right)^{o} - 1$ and $\left(\frac{Y^E}{Y}\right)^{va} - 1$. The output elasticities are calibrated to country-specific input shares, and the VA weights are the VA shares of GDP.

Figure B5 presents aggregate TFP gains when the output elasticities are calibrated to

country-specific input shares and the VA weights are the VA shares of GDP. The results are very similar to those using theory-consistent weights, as using country-specific input shares implicitly assumes no sectoral intermediate-input distortions. Minor differences in the results come only from yearly changes in the sectoral value-added share of gross output, as we calibrate the output elasticities to time-series averages of the sectoral input shares.

C. Recorded Distortions

In this section we show that the bias of the VA approach relative to the GO approach only depends on unrecorded distortions in intermediate-input use. With recorded distortions, our procedure of misallocation accounting results in biased estimates even under the GO approach, but the comparison between the two approaches depends only on unrecorded distortions.

For our purpose, we first decompose the intermediate-input distortion as follows:

$$1 + \tau_{Msi} = (1 + \tau^r_{Msi})(1 + \tau^u_{Msi}),$$

where $1 + \tau^r_{Msi}$ is the part of the distortion that is recorded by the firm as intermediate-input payment; we call it the recorded distortion. $1 + \tau^u_{Msi}$ is the part of the distortion that is not recorded; we call it the unrecorded distortion.

With both recorded and unrecorded distortions, firm value added is now given by

$$P_{Ysi}Y_{si} = \left(1 - \frac{\sigma_s - 1}{\sigma_s}\frac{1-\eta}{1+\tau^u_{Msi}}\right) P_{si}Q_{si}.$$

The only way for firm value added to be proportional to firm output is that all firms within a sector face the same unrecorded distortion. In this case, the VA model can no longer be suitably parameterized such that it is consistent with data generated by the GO model. The two models will produce different aggregate TFP gains in theory.

With both types of distortions, the inference of the primary-input distortions using GO data is correct. However, the inference of the intermediate-input wedges and productivity is distorted even with GO data. For the input wedges, the inference leads to

$$\begin{aligned}
\frac{\sigma_s-1}{\sigma_s}\frac{\alpha_s\eta_s P_{si}Q_{si}}{RK_{si}} &= 1+\tau_{Ksi},\\
\frac{\sigma_s-1}{\sigma_s}\frac{(1-\alpha_s)\eta_s P_{si}Q_{si}}{WL_{si}} &= 1+\tau_{Lsi},\\
\frac{\sigma_s-1}{\sigma_s}\frac{(1-\eta_s)P_{si}Q_{si}}{(1+\tau^r_{Msi})\sum_{q=1}^{S}P_qM_{qsi}} &= 1+\tau^u_{Msi},
\end{aligned}$$

The inference of firm productivity is given by,

$$\kappa_s\frac{(P_{si}Q_{si})^{\frac{\sigma_s}{\sigma_s-1}}}{\left(K_{si}^{\alpha_s}L_{si}^{1-\alpha_s}\right)^{\eta_s}\left((1+\tau^r_{Msi})\sum_{q=1}^{S}P_qM_{qsi}\right)^{1-\eta_s}}=\frac{A_{si}}{(1+\tau^r_{Msi})^{1-\eta_s}},$$

Obviously, the bias in inferring the intermediate-input distortion and firm productivity using GO data comes from the presence of the recorded distortions. Even the GO approach leads to biased measures of the aggregate TFP gain due to incorrect inference.

For the VA model, the inference of the input wedges leads to,

$$\begin{aligned}
\frac{\hat\sigma_s-1}{\hat\sigma_s}\frac{\alpha_s P_{Ysi}Y_{si}}{RK_{si}} &= (1+\tau_{Ksi})\frac{1-\frac{\sigma_s-1}{\sigma_s}\frac{1-\eta_s}{1+\tau^u_{Msi}}}{1-\frac{\sigma_s-1}{\sigma_s}(1-\eta_s)},\\
\frac{\hat\sigma_s-1}{\hat\sigma_s}\frac{(1-\alpha_s)P_{Ysi}Y_{si}}{WL_{si}} &= (1+\tau_{Lsi})\frac{1-\frac{\sigma_s-1}{\sigma_s}\frac{1-\eta_s}{1+\tau^u_{Msi}}}{1-\frac{\sigma_s-1}{\sigma_s}(1-\eta_s)},
\end{aligned}$$

The value-added productivity is inferred as,

$$\widehat{\kappa}_s\frac{(P_{Ysi}Y_{si})^{\frac{\widehat\sigma_s}{\widehat\sigma_s-1}}}{K_{si}^{\alpha_s}L_{si}^{1-\alpha_s}}=\left(\frac{1-\frac{\sigma_s-1}{\sigma_s}\frac{1-\eta_s}{1+\tau^u_{Msi}}}{\eta_s}\right)^{\frac{\widehat\sigma_s}{\widehat\sigma_s-1}}(1+\tau^u_{Msi})^{\frac{\eta_s-1}{1-\frac{\sigma_s-1}{\sigma_s}(1-\eta_s)}}\left(\frac{A_{si}}{(1+\tau^r_{Msi})^{1-\eta_s}}\right)^{\frac{1}{\eta_s}},$$

Hence the difference between the two models in inference arises only from the unrecorded distortions.

With correct parameterization of the model, measured TFP gains only differ in the two

models due to bias in the inference of wedges and productivity. It naturally follows that the measured TFP gain using the VA approach only deviates from that using the GO approach due to unrecorded distortions. Our focus on the bias of the VA approach from the GO approach thus leads us to focus on unrecorded distortions in the paper.

D. Between-Sector Misallocation

D.1 Theoretical Analysis

This section presents further analysis of between-sector misallocation. A previous version of the paper (Hang et al., 2020) establishes that the VA approach would not bias the between-sector misallocation estimates using VA data if there are no between-sector distortions in intermediate inputs.[26] This can be easily shown as follows. For the moment, ignore within-sector firm heterogeneity and assume each sector has a Cobb-Douglas production function in both models. Without between-sector distortions, sectoral value added is related to sectoral output as

$$P_{Ys}Y_s = \eta_s P_s Q_s.$$

This means the between-sector allocation of primary inputs would be the same in the two models. With Cobb-Douglas technology, sectoral TFP does not matter for the measurement of misallocation. We only have to show that the inference of sectoral wedges is not biased under the VA approach. This can be seen from the sectoral counterparts of the first-order conditions for the VA model:

$$\begin{aligned} \frac{\alpha_s P_{Ys} Y_s}{RK_s} &= \mathcal{T}_{Ks}\left(1 - \frac{1-\eta_s}{\mathcal{T}_{Ms}}\right)/\eta_s, \\ \frac{(1-\alpha_s) P_{Ys} Y_s}{WL_s} &= \mathcal{T}_{Ls}\left(1 - \frac{1-\eta_s}{\mathcal{T}_{Ms}}\right)/\eta_s, \end{aligned}$$

[26] This condition also requires a perfectly competitive market structure because even a uniform markup across all sectors induces misallocation of inputs in the production network.

where we have assumed perfect competition. Obviously, the sectoral wedges can be correctly identified. The VA model is then correctly specified and firm productivity and the wedges can be correctly inferred. The VA estimates would not be biased.

The above results crucially depend on correct calibration of model parameters, which could not be identified from sectoral factor shares when wedges are present. Because sectors have different output elasticities, comparison of sectoral MRPs is not possible without correctly calibrated model parameters, as is the case for within-sector comparison. This is one of the main reasons why we focus on within-sector analysis in the empirical analysis in the paper. Studies of between-sector misallocation have to calibrate the output elasticity or estimate the wedges without relying on the first-order conditions. For example, Baqaee and Farhi (2020) identify the wedges with markups and directly estimate markups from data.

Before turning to the empirical analysis, suppose that between-sector distortions in intermediate inputs exist but that the model parameters are known. How would the VA approach bias the estimates of misallocation? As shown in Hang et al. (2020), aggregate TFP can be decomposed into two terms in the GO model: one summarizing primary-input distortions and one summarizing network distortions. The first point to notice is that the VA approach tends to underestimate misallocation because it omits network distortions (the term γ in Hang et al. (2020)). In terms of the allocation of primary inputs, we compare the following two objects using the wedges inferred above.

$$\prod_{s=1}^{S}\left[\left(\frac{\beta_{Ks}^{E}}{\beta_{Ks}}\right)^{\alpha_s\eta_s\tilde{v}_s}\left(\frac{\beta_{Ls}^{E}}{\beta_{Ls}}\right)^{(1-\alpha_s)\eta_s\tilde{v}_s}\right], \text{ and } \prod_{s=1}^{S}\left[\left(\frac{\widehat{\beta}_{Ks}^{E}}{\widehat{\beta}_{Ks}}\right)^{\widehat{\alpha}_s}\left(\frac{\widehat{\beta}_{Ls}^{E}}{\widehat{\beta}_{Ls}}\right)^{1-\widehat{\alpha}_s}\right]^{\widehat{\theta}_s},$$

where efficient allocation requires,

$$\beta_{Ks}^{E}=\frac{\alpha_s\eta_s\tilde{v}_s}{\sum_{q=1}^{S}\alpha_q\eta_q\tilde{v}_q}, \text{ and } \beta_{Ls}^{E}=\frac{(1-\alpha_s)\eta_s\tilde{v}_s}{\sum_{q=1}^{S}(1-\alpha_q)\eta_q\tilde{v}_q},$$

and

$$\widehat{\beta}_{Ks}^{E} = \frac{\widehat{\alpha}_s \widehat{\theta}_s}{\sum_{q=1}^{S} \widehat{\alpha}_q \widehat{\theta}_q}, \text{ and } \widehat{\beta}_{Ls}^{E} = \frac{(1-\widehat{\alpha}_s)\widehat{\theta}_s}{\sum_{q=1}^{S} (1-\widehat{\alpha}_q)\widehat{\theta}_q}.$$

Note that both models would correctly identify $\{\beta_{Ks}, \beta_{Ls}\}$ and $\{\widehat{\beta}_{Ks}, \widehat{\beta}_{Ls}\}$, which are essentially observed between-sector allocation of primary inputs. If the model parameters are correctly calibrated, such that we have $\widehat{\alpha}_s = \alpha_s$, and $\widehat{\theta}_s = \eta_s \tilde{v}_s$ as in Proposition 2, we would also correctly infer the efficient between-sector allocation $\{\beta_{Ks}^{E}, \beta_{Ls}^{E}\}$ and $\{\widehat{\beta}_{Ks}^{E}, \widehat{\beta}_{Ls}^{E}\}$. In this case, the VA approach leads to unbiased results. This is a surprising result which mainly comes from the fact that we do not need the inferred wedges to derive efficient allocation under the VA approach.

A problem with the above analysis is that, in the presence of intermediate-input distortions, it is unclear what the "correct" parameters for the misspecified VA model are. Our analysis above assumes that the parameters are those that would be correct if intermediate-input distortions were absent. We now consider how these parameters are calibrated in the data. The empirical procedure below assumes that we can calibrate the output elasticities using a frictionless economy, the U.S., a practice also used by HK. For the U.S. economy, the output elasticity in the VA model satisfies $\widehat{\alpha}_s = \alpha_s$. Sectoral weights, however, must be calibrated using data that would be distorted by the presence of wedges. Observed allocation is still the same in both models. Efficient allocation in the VA model is now incorrectly inferred, which leads to a lower efficient output and an underestimation of misallocation. However, sectoral weights are also miscalibrated in this case, which biases the VA estimate in an ambiguous direction. Again, we cannot know for sure whether the VA approach underestimates between-sector misallocation of primary inputs.

We assume a uniform intermediate-input wedge applying to all inputs in the GO model, mainly because we do not have industry-specific input use at the firm level. This leads to an underestimation of the cost of misallocation even in the GO model. The VA estimate should contain the same bias because we never consider the effects of intermediate-input distortions

in the VA model. Thus, when we allow for input-specific distortions such that the GO model no longer leads to a biased result, we should expect the VA model to underestimate the cost of misallocation through this channel.

Combining all these discussions, we can conclude that the VA approach has a tendency to underestimate the cost of between-sector misallocation, even though overestimation cannot be ruled out in theory. We next turn to an empirical evaluation of between-sector misallocation in China and India.

D.2 Empirical Analysis

We use the 2005 national Input-Output (IO) tables for the U.S., China, and India from the World Input-Output Database (Timmer et al., 2015) to evaluate between-sector misallocation in China and India. The IO tables cover 56 industries, but not all industries report positive output in the data. The problem is more serious in China and India: 9 industries in the Chinese data and 12 industries in the Indian data report zero output. We thus delete an industry from the IO table if output in this industry is zero for any of the countries, which leaves us with 42 industries.

The IO tables report the use of intermediate inputs separately for domestic and imported inputs. As our model does not take international trade into account, we aggregate domestic and imported inputs, which ensures that we do not mistake trading opportunities for input distortions. We supplement the IO tables with information on capital and labor inputs from the WIOD Socio-Economic Accounts. Together, these two data sources provide a full picture of both primary-input and intermediate-input shares in the data. We calibrate the output elasticities to these shares in the U.S. data in both the GO and VA models. The consumption weights in China and India in the GO model are calibrated to shares of final use, including final consumption, gross fixed capital formation, and changes in inventory in each country. We compute the value-added share of each industry according to the GO model and use these shares as sectoral weights in the VA approach.

Table D1 compares TFP gains under the two approaches. We report two sets of results. In the first set, we assume that intermediate-input distortions are the same for all inputs, as specified in the paper (Columns GO and VA). In this case, the distortions are computed as the average of input distortions weighted by the value of inputs. In the second set, we assume industry-specific input distortions (Columns GO' and VA'). The VA approach underestimates the cost of misallocation for both China and India, but for different reasons. In China, neglecting network distortions has a small impact on the aggregate bias. In India, the bias mainly comes from network distortions. In either case, the bias arising from primary-input distortions does not contribute much to the aggregate bias. This bias is smaller in China, while intermediate-input distortions lead to a much larger aggregate bias in India. When we allow for industry-specific distortions, the GO approach leads to much larger TFP gains, while the estimate under the VA approach does not change much. These results point to the importance of the misallocation of individual inputs, which again would be neglected under the VA approach.

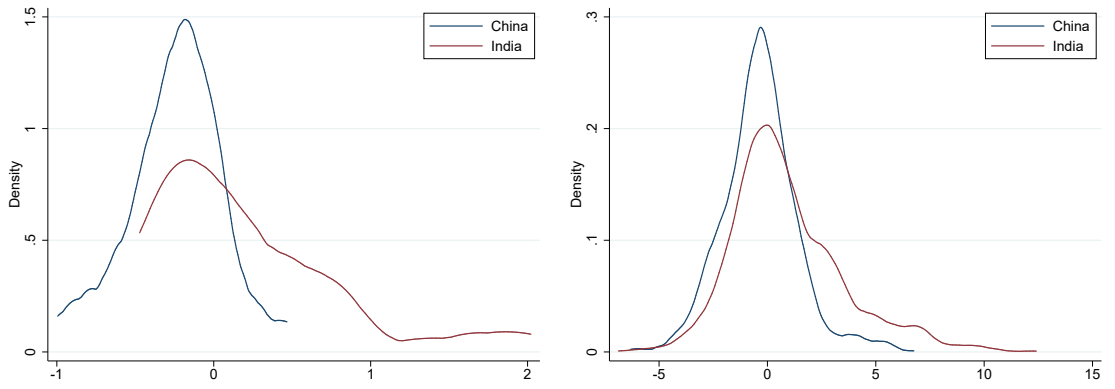
The larger bias under the VA approach for India is again due to large intermediate-input distortions. Figure D1 plots the distributions of both uniform distortions and industry-specific distortions. It can be seen that the distortions are more dispersed for India in either case. These distortions are no longer centered around zero. For India, the uniform distortions mostly lie to the right of zero, indicating that Indian industries have lower intermediate-input shares than the U.S. Correspondingly, the industry-specific distortions also have a larger right tail in the Indian data.

Table D1: Aggregate TFP Gain from Removing Between-Sector Misallocation in Different Models

	China				India			
	GO	VA	GO'	VA'	GO	VA	GO'	VA'
Aggregate	1.1755	1.1103	3.5524	1.1333	1.7617	1.1219	6.0440	1.0873
Intermediate Inputs	1.0005	—	2.5951	—	1.5066	—	4.1364	—
Primary Inputs	1.1749	1.1103	1.3689	1.1333	1.1693	1.1219	1.4612	1.0873

Notes: This table reports aggregate TFP gains from removing all between-sector misallocation for China and India in 2005. For each country, we report results for four models: 1. The GO model with a uniform intermediate-input distortion applying to all industries, as specified in the paper (denoted GO), 2. The associated VA model (denoted VA), 3. The GO model with input-specific distortions (denoted GO'), and 4. The associated VA model (denoted VA'). For the GO models, we also decompose the gains into those due to primary-input distortions and intermediate-input distortions. TFP gain is measured as $\left(\frac{Y^E}{Y}\right)^o$ and $\left(\frac{Y^E}{Y}\right)^{va}$, and the aggregate gain under the GO approach is the product of its two components.

Figure D1: Distribution of Intermediate-Input Distortions



(a) Uniform Distortions (b) Industry-specific Distortions

Note: The left figure plots the distribution of the log of $\mathcal{T}_{Ms}$, the uniform intermediate-input distortion. The right figure plots the distribution of industry-specific input distortions.

References

Acemoglu, D., V. M. Carvalho, A. Ozdaglar, and A. Tahbaz-Salehi (2012). The Network Origins of Aggregate Fluctuations. Econometrica 80(5), 1977–2016.

Adamopoulos, T., L. Brandt, J. Leight, and D. Restuccia (2022). Misallocation, Selection, and Productivity: A Quantitative Analysis with Panel Data from China. Econometrica 90(3), 1261–1282.

Alfaro, L., A. Charlton, and F. Kanczuk (2009). Plant Size Distribution and Cross-Country Income Differences. NBER International Seminar on Macroeconomics 5(1), 243–272.

Altinoglu, L. (2021). The Origins of Aggregate Fluctuations in a Credit Network Economy. Journal of Monetary Economics 117, 316–334.

Asker, J., A. Collard-Wexler, and J. D. Loecker (2014). Dynamic Input and Resource (Mis)Allocation. Journal of Political Economy 122(5), 1013–1063.

Atalay, E. (2014). Materials Prices and Productivity. Journal of the European Economic Association 12(3), 575–611.

Banerjee, A. V. and E. Duflo (2005). Growth Theory through the Lens of Development Economics. In Handbook of Economic Growth, Volume 1, Chapter 7, pp. 473–552. Elsevier.

Baqaee, D. R. and E. Farhi (2019a). Macroeconomics with Heterogeneous Agents and Input-Output Networks. Working Paper.

Baqaee, D. R. and E. Farhi (2019b). Network, Barriers, and Trade. Working Paper.

Baqaee, D. R. and E. Farhi (2020). Productivity and Misallocation in General Equilibrium. Quarterly Journal of Economics 135(1), 105–163.

Bartelme, D. and Y. Gorodnichenko (2015). Linkages and Economic Development. Technical report, National Bureau of Economic Research.

Bartelsman, E., J. Haltiwanger, and S. Scarpetta (2013). Cross-Country Differences in Productivity: The Role of Allocation and Selection. American Economic Review 103(1), 305–334.

Basu, S. and J. G. Fernald (1995). Are Apparent Productive Spillovers a Figment of Specification Error? Journal of Monetary Economics 36(1), 165–188.

Basu, S. and J. G. Fernald (1997). Returns to Scale in U.S. Production: Estimates and Implications. Journal of Political Economy 105(2), 249–283.

Basu, S. and J. G. Fernald (2002). Aggregate Productivity and Aggregate Technology. European Economic Review 46, 963–991.

Bigio, S. and J. La'O (2020). Distortions in Production Networks. Quarterly Journal of Economics 135(4), 2187–2253.

Bils, M., P. J. Klenow, and C. Ruane (2021). Misallocation or Mismeasurement? Journal of Monetary Economics 124, S39–S56.

Brandt, L., T. Tombe, and X. Zhu (2013). Factor market distortions across time, space, and sectors in china. Review of Economic Dynamics 16, 39–58.

Bridgman, B. and B. Herrendorf (2021). Markups, Input-Output Linkages and Structural Change: Evidence from the National Accounts. Working Paper.

Broda, C. and D. E. Weinstein (2006). Globalization and the Gains from Variety. The Quarterly Journal of Economics 121(2), 541–585.

Bruno, M. (1978). Duality, Intermediate Inputs and Value-added. In Contributions to Economic Analysis, Volume 2, pp. 3–16. Elsevier.

Bruno, M. (1984). Raw Materials, Profits, and the Productivity Slowdown. The Quarterly Journal of Economics 99(1), 1–29.

Buera, F. J. and Y. Shin (2013). Financial Frictions and the Persistence of History: A Quantitative Exploration. Journal of Political Economy 121(2), 221–272.

Caliendo, L., F. Parro, and A. Tsyvinski (2022). Distortions and the Structure of the World Economy. American Economic Journal: Macroeconomics 14(4), 274–308.

Chen, C., D. Restuccia, and R. Stantaeulàlia-Llopis (2022). Land Misallocation and Productivity. American Economic Journal: Macroeconomics. Forthcoming.

Chen, K. and A. Irarrazabal (2015). The Role of Allocative Efficiency in a Decade of Recovery. Review of Economic Dynamics 18(3), 523–550.

David, J. and V. Venkateswaran (2019). The Sources of Capital Misallocation. American Economic Review 109(7), 2531–2567.

Dias, D. A., C. R. Marques, and C. Richmond (2016). Misallocation and Productivity in the Lead Up to the Eurozone Crisis. Journal of Macroeconomics 49, 46–70.

Domar, E. D. (1961). On the Measurement of Technological Change. The Economic Journal 71(284), 709–729.

Dong, B. (2011). Misallocation or Mismeasurement? Evidence from Plant-Level Data. Ph. D. thesis, New York University.

Gandhi, A., S. Navarro, and D. Rivers (2017, May). How Heterogeneous is Productivity? A Comparison of Gross Output and Value Added? Working Paper.

Ghatak, M. and D. Mookherjee (2025). Misallocating misallocation? Annual Review of Economics 17, 511–538.

Gollin, D. and C. Udry (2021). Heterogeneity, Measurement Error, and Misallocation: Evidence from African Agriculture. Journal of Political Economy 129(1), 1–80.

Gopinath, G., Ş. Kalemli-Özcan, L. Karabarbounis, and C. Villegas-Sanchez (2017). Capital Allocation and Productivity in South Europe. The Quarterly Journal of Economics 132(4), 1915–1967.

Guner, N., G. Ventura, and Y. Xu (2008). Macroeconomic Implications of Size-dependent Policies. Review of Economic Dynamics 11(4), 721–744.

Haltiwanger, J., R. Kulick, and C. Syverson (2018). Misallocation Measures: The Distortion That Ate the Residual. NBER Working Paper 24199.

Hang, J., P. Krishna, and H. Tang (2020). Input-Output Networks and Misallocation. Technical report. NBER Working Paper No. w27983.

Hendel, I. and A. Nevo (2006). Measuring the Implications of Sales and Consumer Inventory Behavior. Econometrica 74(6), 1637–1673.

Herrendorf, B., R. Rogerson, and A. Valentinyi (2013). Two Perspectives on Preferences and Structural Transformation. American Economic Review 103(7), 2752–2789.

Hopenhayn, H. A. (2014). Firms, Misallocation, and Aggregate Productivity: A Review. Annual Review of Economics 6(1), 735–770.

Hsieh, C.-T. and P. J. Klenow (2009). Misallocation and Manufacturing TFP in China and India. The Quarterly Journal of Economics 124(4), 1403–1448.

Hsieh, C.-T. and P. J. Klenow (2014). The Life Cycle of Plants in India and Mexico. The Quarterly Journal of Economics 129(3), 1035–1084.

Hulten, C. R. (1978). Growth Accounting with Intermediate Inputs. The Review of Economic Studies 45(3), 511–518.

Jones, C. I. (2011). Intermediate Goods and Weak Links in the Theory of Economic Development. American Economic Journal: Macroeconomics 3(2), 1–28.

Jones, C. I. (2013). Misallocation, Economic Growth, and Input-Output Economics. In Advances in Economics and Econometrics, Tenth World Congress, Volume 2. Cambridge University Press.

Kalemli-Ozcan, S. and B. E. Sorensen (2012). Misallocation, Property Rights, and Access to Finance: Evidence from Within and Across Africa. Technical report, National Bureau of Economic Research.

Liu, E. (2019). Industrial Policies in Production Networks. Quarterly Journal of Economics 134(4), 1883–1948.

Long, J. B. J. and C. I. Plosser (1983). Real Business Cycles. Journal of Political Economy 91(1), 39–69.

Luo, S. (2019). Propagation of Financial Shocks in an Input-output Economy with Trade and Financial Linkages of Firms. Review of Economic Dynamics 36, 246–269.

National Bureau of Statistics (2007). Chinese GDP Accounting Methods in Census Years. Beijing: Chinese Statistics Press. In Chinese.

National Bureau of Statistics (2008). Chinese GDP Accounting Methods in Non-Census Years. Beijing: Chinese Statistics Press. In Chinese.

Oberfield, E. (2013). Productivity and Misallocation during a Crisis: Evidence from the Chilean Crisis of 1982. Review of Economic Dynamics 16, 100–119.

Osotimehin, S. and L. Popov (2023). Misallocation and intersectoral linkages. Review of Economic Dynamics. Forthcoming.

Restuccia, D. and R. Rogerson (2008). Policy Distortions and Aggregate Productivity with Heterogenous Establishments. Review of Economic Dynamics 11, 707–720.

Restuccia, D. and R. Rogerson (2013). Misallocation and Productivity. Review of Economic Dynamics 16, 1–10.

Sato, K. (1976). The Meaning and Measurement of the Real Value Added Index. The Review of Economics and Statistics 58(4), 434–442.

Song, Z. M. and G. L. Wu (2015). Identifying capital misallocation. Working Paper.

Timmer, M. P., E. Dietzenbacher, B. Los, R. Stehrer, and G. J. De Vries (2015). An Illustrated User Guide to the World Input-Output Database: The Case of Global Automotive Production. Review of International Economics 23(3), 575–605.

Wang, W. and J. Xu (2025). Financing Intermediate Inputs and Misallocation. Macroeconomic Dynamics 29, e89.

Ziebarth, N. L. (2013). Are China and India Backward? Evidence from the 19th Century U.S. Census of Manufactures. Review of Economic Dynamics 16, 86–99.