

The Aggregate Importance of Intermediate Input Substitutability

Alessandra Peter
Stanford University

Cian Ruane *
Research Department, IMF

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Abstract

Should economic development policies target specific sectors of the economy or follow a ‘big push’ approach of advancing all sectors together? The relative success of these strategies is determined by how easily firms can substitute between intermediate inputs sourced from different sectors of the economy: a low degree of substitutability increases the costs from ‘bottleneck’ sectors and the need for ‘big push’ policies. In this paper, we estimate long-run elasticities of substitution between intermediate inputs used by Indian manufacturing plants. We use detailed data on plant-level intermediate input expenditures, and exploit reductions in import tariffs as plausibly exogenous shocks to domestic intermediate input prices. We find a long-run plant-level elasticity of substitution of 4.3, much higher substitutability than existing short-run estimates or the Cobb-Douglas benchmark. To quantify the aggregate importance of intermediate input substitution, we embed our elasticities in a general equilibrium model with heterogeneous firms, calibrated to plant- and sector-level data for the Indian economy. We find that the aggregate gains from a 50% productivity increase in any one Indian manufacturing sector are on average 47% larger with our estimated elasticities. Our counterfactual exercises highlight the importance of intermediate input substitution in amplifying policy reforms targeting individual sectors.

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1. Introduction

The production of goods requires a range of intermediate inputs from other sectors of the economy; manufacturing and selling a shirt requires material inputs such as cotton and dyes, energy inputs such as electricity, and service inputs such as distribution services. [Leontief \(1936\)](#) and [Hirschman \(1958\)](#) reasoned that such inter-industry linkages could be important for understanding the process of economic development and the effects of economic policy reforms.¹ While there has been recent renewed interest in this literature ([Bartelme and Gorodnichenko \(2015\)](#), [Fadinger et al. \(2016\)](#), [Liu \(2017\)](#)), the role of substitutability between intermediate inputs has remained theoretical and qualitative ([Jones \(2011\)](#)). An important reason for this is a lack of evidence regarding the substitutability between intermediate inputs in the long-run. Existing empirical evidence suggests that intermediate inputs may not be easy to substitute around in the short-run.² In the long run, however, firms can substitute between intermediate inputs in a variety of ways; through the purchasing of new equipment, targeted innovation, reduction of waste or the re-organization of production. How these long-run substitution possibilities affect the aggregate gains from productivity growth or policy reforms in individual sectors is a quantitative question which we attempt to answer in this paper.

Our main contribution is to provide estimates of elasticities of substitution between intermediate inputs at a 6-8 year horizon.³ We use the 1989-1997 years of the Indian Annual Survey of Industries (ASI), a dataset containing detailed information on plant-level intermediate input use. We derive a structural estimating equation based on nested constant elasticity of substitution (CES) production. The upper nest of intermediate inputs comprises energy, materials and services, while the lower nest of material inputs comprises 9 broad categories of materials.⁴ The estimating equations are simple linear regressions of (log-)changes in relative input expenditures on (log-)changes in relative input prices. We instrument for changes in input prices using changes in tariffs following India's trade liberalization in 1991. Our estimate of the plant-level elasticity of substitution between material input categories is 4.3. The 95% confidence interval is [2.4,6.1], lying significantly above the commonly used Cobb-Douglas benchmark. Our estimate of the plant-level elasticity of substitution between energy, materials and services is 0.9, and not statistically distinguishable from one.

¹[Leontief \(1936\)](#) states: "It is true that, from the point of view of welfare economics, the part of the annual flow of values which is more less arbitrarily defined as the National Income deserves particular attention. To a more detached observer, however, it may appear to be a mere by-product of the whole highly complex process of production and distribution of economic values."

²[Boehm et al. \(2016\)](#), [Barrot and Sauvagnat \(2016\)](#) and [Atalay \(2017\)](#) estimate a high degree of complementarity (low degree of substitutability) between intermediate inputs in the short run.

³We will refer to these as long-run elasticities, though we acknowledge that these could equally be described as medium/long-run elasticities.

⁴Example categories include 'Base Metals', 'Rubber and Plastics' and 'Wood, Pulp and Paper Products'.

Our second contribution is to evaluate the importance of substitution between intermediate inputs for a range of policy counterfactuals. We embed our elasticity estimates in a quantitative general equilibrium model with input-output linkages (following [Long and Plosser \(1983\)](#) and [Horvath \(1998\)](#)), heterogeneous firms facing distortionary taxes and elasticities of substitution that differ from unity. Firms produce output using labor and intermediate inputs from each sector. These intermediate inputs can be sourced domestically or imported. Firms have idiosyncratic productivities and distortions. The distortions take the form of a tax on revenues and reduce aggregate TFP by creating a misallocation of inputs across firms and sectors. Sectoral output can be used as an intermediate input or consumed by the representative consumer.

We calibrate our model to match plant-level data from the ASI, markup estimates for Indian manufacturing firms from [De Loecker et al. \(2016\)](#), as well as sector-level data from the World Input-Output Database (WIOD). For our first set of counterfactual exercises, we calculate the welfare gains from a 50% productivity increase in each one of our 29 sectors individually. We find that the average aggregate consumption gains are 40% larger in a model with our estimated elasticities relative to the Cobb-Douglas benchmark, and 56% larger relative to a model with typical short-run elasticities. This amplification is larger in manufacturing (64%) than in services (32%), and stems from non-linearities in the relationship between sectoral productivity shocks and aggregate consumption. Similarly to [Baqae and Farhi \(2017\)](#), we find that these second- (higher-) order effects can have an important impact on aggregate consumption.

In our second set of counterfactuals, we calculate the welfare gains from removing dispersion in distortions, both across plants within sectors and across sectors. We find that the welfare gains from removing all distortions are 16% assuming unitary elasticities of substitution between intermediate inputs, and 20% with our estimated elasticities. Our elasticity estimates matter more for counterfactuals involving reductions in across-sector dispersion in distortions than within-sector dispersion in distortions. Our final set of counterfactuals involve calculating the forecasted welfare gains from the Indian trade liberalization. We calculate the welfare gains to be 2.4% with unitary elasticities of substitution, and 2.7% with our estimated elasticities.

Our counterfactual exercises illustrate that the aggregate gains from policy reforms affecting specific sectors could be amplified through intermediate input substitution. This is relevant for reforms such as trade liberalizations as well as labor and product market deregulations.

1.1. Related Literature

Our paper contributes to the macroeconomics literature on inter-sectoral linkages and firm networks. A large branch of this literature analyses the role of linkages in driving business cycle fluctuations by amplifying shocks to individual firms or industries.⁵ Closely related to our paper, [Baqae and Farhi \(2017\)](#) show how non-unitary elasticities of substitution imply that sectoral productivity shocks have a non-linear impact on aggregate output. Our contribution is complementary to theirs; while they focus on how short-run complementarities affect business cycles, we focus on how long-run substitutability affects economic development and the impact of policy reforms.

Our paper also relates to the literature incorporating frictions in macroeconomic models with production networks.⁶ Most closely related to our paper, [Caliendo et al. \(2017\)](#) evaluate the effects of distortions in the world input-output matrix, allowing for an elasticity of substitution between intermediate inputs greater than one. In contrast, we focus on the impact of policy changes in one particular country, and on the additional amplification coming from high substitutability between intermediate inputs. Also related to our paper, [Liu \(2017\)](#) develops a sufficient statistic approach, under weak functional form assumptions, to evaluate the aggregate welfare gains from marginal industrial policy subsidies to specific sectors. We impose stricter functional form assumptions (CES) but take into account the non-linear impact of policy reforms on welfare. We find that these nonlinearities are quantitatively important in our counterfactuals. [Jones \(2011\)](#) examines the role of both distortions and complementarities between intermediate inputs in explaining cross-country differences in development. Rather than attempting to explain the observed gaps in GDP per capita between India and the U.S., we take a quantitative approach to evaluating counterfactual gains from productivity increases or policy reforms in specific sectors.

Our paper is related to a number of studies estimating structural elasticities of substitution for use in macroeconomic and trade models.⁷ Most closely related to this paper, the empirical literature on intermediate input linkages has estimated short-run elasticities of substitution between intermediate inputs near the Leontief lower bound of 0.⁸ Our

⁵Important papers in this literature include [Gabaix \(2011\)](#) and [Acemoglu et al. \(2012\)](#).

⁶Recent contributions in this literature include [Leal \(2015\)](#), [Bigio and La'O \(2016\)](#), [Grassi \(2017\)](#), [Altinoglu \(2017\)](#) and [Baqae \(2017\)](#). We model frictions as revenue taxes or subsidies following the literature on input misallocation (see [Hopenhayn \(2014\)](#) for a review).

⁷[Redding and Weinstein \(2016\)](#) and [Hobijn and Nechio \(2017\)](#) estimate elasticities of substitution across consumption goods at various levels of aggregation. [Broda and Weinstein \(2006\)](#) estimate elasticities of substitution across imported consumption goods. On the production side, studies have estimated the elasticities of substitution between; domestic and imported inputs ([Blaum et al. \(2016\)](#)), capital and labor ([Raval \(2017\)](#), [Oberfield and Raval \(2014\)](#)), and capital/labor and intermediates ([Oberfield and Raval \(2014\)](#), [Atalay \(2017\)](#), [Miranda-Pinto and Young \(2017\)](#), [Chan \(2017\)](#), [Doraszelski and Jaumandreu \(Forthcoming\)](#)).

⁸[Boehm et al. \(2016\)](#), [Barrot and Sauvagnat \(2016\)](#) and [Atalay \(2017\)](#) show evidence of low substitutability.

elasticity estimates are at a longer time horizon, 6-8 years, and exploit large permanent shocks to prices for identification. Leontief short-run elasticities of substitution are perfectly consistent with our long-run estimates. However, our estimates of long-run elasticities are needed to analyze the long-run effects of policy reforms and sectoral productivity improvements. Also related to our paper, [Asturias et al. \(2017\)](#) use a subset of reported intermediate inputs from the ASI to estimate across-industry elasticities of substitution ranging from 1.2 to 1.99.⁹ Our empirical strategy differs in that we directly estimate the plant-level elasticity of substitution (using within-plant time-series variation in expenditure shares). Our instrumental variables strategy also addresses the multiple sources of bias involved in OLS estimation of structural elasticities.

Finally, our paper builds on a considerable literature examining the effects of India's trade liberalization, and also relates to the literature evaluating the gains from trade in intermediate inputs.^{10 11}

1.2. Outline

The rest of the paper is structured as follows. In Section 2 we present a model of plant-level production which motivates our empirical strategy. In Section 3 we present our data. In Section 4 we discuss our empirical strategy. In Section 5 we show the results from our elasticity estimation. In Section 6 we go through our quantitative macroeconomic model, and in Section 7 we conduct our counterfactual exercises.

2. Theoretical Model

We assume that the production function for plant i in period t takes the following constant elasticity of substitution (CES) functional form:

$$Q_{it} = A_{it} \left(\gamma_{it} F(L_{it}, K_{it})^{\frac{\varepsilon-1}{\varepsilon}} + (1 - \gamma_{it}) X_{it}^{\frac{\varepsilon-1}{\varepsilon}} \right)^{\frac{\varepsilon}{\varepsilon-1}}$$

Plant i produces output Q_{it} in period t using a CES composite of a capital-labor (or value-added) bundle $F(L_{it}, K_{it})$ and an intermediate input bundle X_{it} . ε is the elasticity of

⁹[Asturias et al. \(2017\)](#) exploit cross-sectional variation in district-level expenditures and transportation costs for identification. Using a subsample of inputs produced by monopolists, they run an OLS regression of district-level input expenditures on measures of transportation costs to identify the across-industry elasticity of substitution.

¹⁰Researchers have used India's trade liberalization to study the effects of trade on poverty ([Topalova \(2010\)](#)), productivity and reallocation ([Sivadasan \(2009\)](#) and [Topalova and Khandelwal \(2011\)](#)), product range ([Goldberg et al. \(2010\)](#)) and markups ([De Loecker et al. \(2016\)](#)).

¹¹Important papers emphasizing the importance of intermediate input trade include [Amiti and Konings \(2007\)](#), [Blaum et al. \(2016\)](#), [Caliendo and Parro \(2015\)](#), [Ossa \(2015\)](#) and [Tintelnot et al. \(2017\)](#).

substitution between the value-added bundle and the intermediate input bundle. γ_{it} is a value-added augmenting technological shifter. The intermediate input bundle X_{it} has a nested CES structure. The upper nest consists of energy (E_{it}), material (M_{it}) and service (S_{it}) input bundles:¹²

$$X_{it} = \left[\pi_{it}^e E_{it}^{\frac{\theta-1}{\theta}} + \pi_{it}^m M_{it}^{\frac{\theta-1}{\theta}} + \pi_{it}^s S_{it}^{\frac{\theta-1}{\theta}} \right]^{\frac{\theta}{\theta-1}}$$

θ is the elasticity of substitution between energy, materials and fuels. π_{it}^e , π_{it}^m and π_{it}^s are input-biased technological shifters. Each of E_{it} , M_{it} and S_{it} are CES aggregates of energy, material and service inputs: E_{ikt} , M_{ikt} , S_{ikt} :

$$Z_{it} = \left[\sum_{k \in \kappa_{it}^z} \pi_{ikt}^z Z_{ikt}^{\frac{\theta^z-1}{\theta^z}} \right]^{\frac{\theta^z}{\theta^z-1}} \quad \text{where } Z \in \{E, M, S\}$$

θ^e , θ^m and θ^s are the elasticities of substitution within each nest. As before π_{ikt}^e , π_{ikt}^m and π_{ikt}^s are input-biased technological shifters. κ_{it}^e , κ_{it}^m and κ_{it}^s are the set of energy, material and service inputs used by each plant i in period t . The set of inputs used may vary both across plants and over time, though we do not explicitly model this extensive margin choice. Cobb-Douglas production functions are a special case where all the elasticities of substitution equal 1. In this limiting case the technological shifters γ and π (appropriately normalized) are the exponents in the Cobb-Douglas production functions. To derive our estimating equations we assume that plants are cost-minimizing and take input prices as given. However, we do not need to impose structure on the demand-side. Input prices may vary across plants, who solve the following problem:

$$\min_{K_{it}, L_{it}, \{Z_{ikt}\}} R_{it}K_{it} + w_{it}L_{it} + \sum_{k \in \kappa_{it}^e} P_{ikt}^e E_{ikt} + \sum_{k \in \kappa_{it}^m} P_{ikt}^m M_{ikt} + \sum_{k \in \kappa_{it}^s} P_{ikt}^s S_{ikt}$$

such that $Q_{it} \geq Q$. Taking first-order conditions and re-arranging we get the following log-linear relationships between expenditure shares on material inputs and the relative price of material inputs:

$$\ln \left(\frac{P_{ikt}^m M_{ikt}}{P_{it}^m M_{it}} \right) = (1 - \theta_m) \ln \left(\frac{P_{ikt}^m}{P_{it}^m} \right) + \theta_m \ln(\pi_{ikt}^m) \quad (1)$$

¹²This choice of an upper nest is consistent with the ‘KLEMS’ approach to national accounting (<http://www.worldklems.net/index.htm>) and the reporting of intermediate inputs in the Indian micro-data.

P_{it}^m is the CES price index for material inputs for plant i .¹³ From Equation 1 it is clear that two plants facing the same input prices could have different expenditure shares if they have different π_{ikt}^m . The expenditure share on materials relative to energy (services) is log-linearly related to the relative price of materials and energy (services):

$$\ln \left(\frac{P_{it}^m M_{it}}{P_{it}^e E_{it}} \right) = (1 - \theta) \ln \left(\frac{P_{it}^m}{P_{it}^e} \right) + \theta \ln \left(\frac{\pi_{it}^m}{\pi_{it}^e} \right)$$

Taking changes over time (and dropping time subscripts) we have that:

$$\Delta \ln \left(\frac{P_{ik}^m M_{ik}}{P_i^m M_i} \right) = (1 - \theta_m) \Delta \ln \left(\frac{P_{ik}^m}{P_i^m} \right) + \theta_m \Delta \ln (\pi_{ik}^m) \quad (2)$$

$$\Delta \ln \left(\frac{P_i^m M_i}{P_i^e E_i} \right) = (1 - \theta) \Delta \ln \left(\frac{P_i^m}{P_i^e} \right) + \theta \Delta \ln \left(\frac{\pi_i^m}{\pi_i^e} \right) \quad (3)$$

Equations 2-3 form the basis for our empirical estimation of the within materials elasticity of substitution (θ_m) and the elasticity of substitution between energy, materials and services (θ).¹⁴ Under the Cobb-Douglas benchmark of $\theta = \theta_m = 1$, expenditure share changes are independent of price changes. If price increases induce an increase (decrease) in expenditure shares, this is a sign of complementarities (substitutability). Estimating these parameters requires data on plant-level intermediate input expenditures as well as data on input prices. Due to the possibility that changes in the technological shifters (π_{ki}^m) are correlated with changes in prices (simultaneity bias), and the possibility of measurement error in input prices (attenuation bias), OLS estimates of the elasticities are likely to be biased and inconsistent. We therefore use changes in import tariffs as an instrumental variable when estimating these equations in 2SLS. In Section 3 we lay out the data we use in the paper, and in Section 4 we discuss in more detail our empirical specification and identification strategy.

3. Data

3.1. Plant-level Expenditures on Intermediate Inputs

We obtain data on plant-level intermediate input expenditures from the Indian Annual Survey of Industries (ASI). The ASI is a nationally representative yearly survey of formal

¹³The formula is given by: $P_{it}^m = \left(\sum_{k \in \kappa_{it}^z} (\pi_{ikt}^z)^{\theta_m} P_{ikt}^m \right)^{\frac{1}{1-\theta_m}}$

¹⁴Our identification strategy will enable us to identify these two parameters, but not θ_e or θ_s . In future versions of the paper we will estimate ϵ using a similar specification.

Indian manufacturing plants.¹⁵ The coverage of the survey is all plants with more than 10 workers using power and all plants with more than 20 workers not using power. Only the ‘detailed’ versions of the ASI contain information on the values and quantities reported by plants for each of their intermediate inputs. Given India’s trade liberalization began in 1991, we restrict our attention to the detailed ASI surveys between 1989 and 1997.¹⁶ More details on the ASI are available in Appendix A4..

Intermediate inputs are reported under three broad groupings: energy, material and service inputs. Imports and domestic purchases of materials are reported separately. Service inputs are classified into five broad categories (e.g. banking charges) and energy inputs are classified into 13 broad categories (e.g. purchased electricity).¹⁷ From 1995 onwards, expenditures on material inputs are reported according to the Annual Survey of Industries Commodity Classification (ASICC). Materials are aggregated into the nine categories shown in Table 1 (e.g. Chemicals).¹⁸ Prior to 1995, expenditures on material inputs are reported according to the ‘ASI Item Code’ classification. We construct a detailed concordance from the ‘ASI Item Code’ classification to the ASICC classification.¹⁹

Average spending shares on each intermediate input category are reported in Table 1. Material inputs make up close to 75% of intermediate input expenditures. The most important categories of material input expenditures are ‘Animal & Vegetable Products, Beverages & Tobacco’ and ‘Base Metals, Machinery Equipment & Parts’, making up 19.8% and 32.7% of average expenditures respectively.²⁰ We also report the within-industry standard deviations of input spending shares in Table 1. There is a considerable amount of dispersion; 24.6% for the average material input category. While measurement error is likely to be an important source of dispersion, this is also suggestive evidence that there is heterogeneity in the production technologies used by Indian manufacturing plants producing similar products.

¹⁵The surveys cover accounting years (e.g. 1989-1990), but we will refer to each survey by the earlier of the two years covered.

¹⁶1989 is the earliest year in which a detailed ASI survey is available. In addition, detailed ASI surveys are not available between 1990 and 1992. We don’t use the 1998 and 1999 ASI surveys because of changes in the reporting of intermediate inputs in those years. In addition, concerns regarding the endogeneity of import tariff changes are more important beyond 1997 (Topalova and Khandelwal (2011)).

¹⁷See Table 11 for a list of all the input categories.

¹⁸These nine product/input categories correspond to the one-digit ASICC codes (ASICC1). These ASICC1 codes are further disaggregated into 350 three-digit codes (ASICC3) and 5,456 five-digit codes (ASICC5).

¹⁹Our concordance captures 80% of aggregate materials expenditure in 1989. Table 12 provides examples of our concordance from the 1989 ASI item codes to ASICC codes. See Section A2. for more details.

²⁰A number of products belonging to the ‘Base Metals, Machinery Equipment & Parts’ category would be most appropriately classified as capital equipment. However we restrict our attention to inputs reported in the ‘material inputs’ section of the ASI survey, which is separate from where firms report the value of the fixed capital stock.

Table 1: Spending Shares on Intermediate Inputs in the ASI

Intermediate Input Categories	Spending Shares	
	Average (%)	Std. Dev. (%)
Energy	17.4	19.2
Materials	75.2	20.7
1. Animal / Vegetable Products	14.9	18.4
2. Ores & Minerals	5.7	33.8
3. Chemicals	7.6	30.0
4. Rubber, Plastic, Leather	5.3	25.4
5. Wood, Cork, Paper	6.1	23.5
6. Textiles	9.1	24.0
7. Base Metals & Machinery	24.6	19.9
8. Transport Equipment	0.2	23.9
9. Other manufactured articles	1.7	27.8
Services	7.4	10.4

Notes: Average shares are across all plants and industries in 1989, 1995, 1996 and 1997, and then averaged across all years. The standard deviation of spending shares is the across-industry (weighted) average of within-industry dispersion.

3.2. Intermediate Input Prices

Materials

We use the Indian wholesale price index (WPI) series as our measure of material input prices.²¹ These are factory-gate prices of 447 products produced by Indian plants; domestically produced goods. We prefer the WPI to unit values (expenditures/quantities) constructed from the ASI because we need measures of quality-adjusted input prices.²²

In order to construct price indices for each of the nine categories of material inputs, we proceed as follows. We first construct a concordance between the WPI product codes and the three-digit ASICC sub-categories of material inputs (e.g. ‘Organic Chemicals’ and ‘Inorganic Acids’ are sub-categories of the ‘Chemicals’ category).²³ Next, we use plant (industry) spending shares as weights to construct plant- (industry-) specific Tornqvist price indices for each of the nine categories of material inputs. Denoting by k a material input category (e.g. Chemicals) and by l a three-digit material sub-category (e.g. Inorganic

²¹The WPI series can be downloaded here: <http://eaindustry.nic.in/home.asp>

²²Unit values are often used as a proxy of product quality in the trade literature. As will be discussed in more detail in Section 4., unobserved input quality will be a source of bias in our estimation.

²³We concord 353 WPI product codes to 100 ASICC3 codes. Examples of the concordance are shown in Table 13. See Appendix A3. for more details.

Acids), we construct a plant-specific Tornqvist price index for plant i between 1989 and year t as follows:

$$\Delta \ln(\tilde{P}_{ik,t}^m) = \sum_l \frac{1}{2} (w_{ikl,t} + w_{ikl,1989}) \Delta \ln(\tilde{P}_{kl,t}^m)$$

where $\Delta \ln(\tilde{P}_{kl}^m)$ is the measured change in the WPI for the material sub-category l , and $w_{ikl,t}$ is plant i 's spending share on l in period t . Plants (or industries) will have different measured price indices provided that they differ in their exposures to different sub-categories of material inputs.²⁴ Similarly, we construct the material input bundle price index for plant i (or industry j) by weighting the price changes of each category of material inputs by average plant (industry) spending shares ($w_{ik,t}$):

$$\Delta \ln(\tilde{P}_{i,t}^m) = \sum_l \frac{1}{2} (w_{ik,t} + w_{ik,1989}) \Delta \ln(\tilde{P}_{ik,t}^m)$$

Energy and Services

We use expenditure and quantity data on energy inputs from the ASI to construct plant- (industry-) specific price indices for the energy input bundle. We construct yearly prices for each category of energy inputs (e.g. coal) by taking the median unit value across plants.²⁵ We obtain yearly prices for each category of service inputs (e.g. banking) from the World KLEMS database for India.²⁶ We then construct the Tornqvist price index for the energy and service input bundles by weighting the price changes for each category of energy and service inputs by plant (industry) spending shares:

$$\Delta \ln(\tilde{P}_{i,t}^z) = \sum_l \frac{1}{2} (w_{ik,t}^z + w_{ik,1989}^z) \Delta \ln(\tilde{P}_{k,t}^z) \quad \text{where } Z \in \{E, S\}$$

where k is the energy/service input category and $w_{ik,t}^z$ is the plant spending share in year t .

3.3. Import Tariffs on Material Inputs

Our dataset of Indian import tariffs at the six-digit level (HS6) is the same as that used in Topalova (2010) and Topalova and Khandelwal (2011).²⁷ We link tariffs to the WPI classification through a concordance available in Topalova (2010) Using our WPI-ASICC con-

²⁴An additional requirement is that the changes in the WPI differ across the sub-categories of materials.

²⁵We use the median unit values across plants in order to average out measurement error in unit values for each category of energy inputs.

²⁶The KLEMS series can be downloaded here: <http://www.worldklems.net/data.htm>. We create a concordance linking the classification of service inputs in the ASI (banking, communication, distribution, insurance and printing) to that in World KLEMS.

²⁷We are very grateful to the authors for having shared their data with us.

cordance, we then construct an import tariff measure for each three-digit sub-category of material inputs.

When constructing plant- (industry-) specific import tariff measures for each category of material inputs, we follow a similar approach to the one we used when constructing price indices; we weight the changes in import tariffs at the sub-category level by plant (industry) spending shares. There are two main differences between how we construct the import tariff instrument and how we construct the material input price indices. The first difference is that we use 1989 spending shares as weights rather than Tornqvist shares (average of pre- and post-). We therefore avoid any potential source of bias arising from using post-reform expenditure shares in our instrument. The second difference is that, when constructing the instrument at the industry-level, we use ‘leave-one-out’ industry shares: we drop plant i when constructing the industry shares that go into constructing the instrument for plant i . This avoids any mechanical correlation between our instrument and our dependent variable through pre-reform plant expenditures shares. The exact formula for the tariff instrument with plant-specific weights is as follows:

$$\Delta \ln(1 + \tilde{\tau}_{ik,t}) = \sum_l w_{ikl,1989} \Delta \ln(1 + \tilde{\tau}_{kl,t})$$

We will revisit these measurement issues and the implications for our estimation in the next section, where we lay out the details of our estimation strategy.

4. Estimation Strategy

4.1. Empirical Specifications

Equation 2 provides the theoretical basis for the following 2SLS empirical specification:

$$\text{First stage: } \Delta \ln(\tilde{P}_{jik}^m) = \rho_m \Delta \ln(1 + \tilde{\tau}_{jik}) + \lambda_{ji} + \eta_{jik} \quad (4)$$

$$\text{Second stage: } \Delta \ln(\tilde{P}_{jik}^m \tilde{M}_{jik}) = \beta_m \Delta \ln(\tilde{P}_{jik}^m) + \lambda_{ji} + \epsilon_{jik} \quad (5)$$

A \sim over a variable indicates that it is measured in the data as opposed to the true value in our theoretical model. i indicates a plant, j a 4-digit NIC87 industry, and k a material input category. $\tilde{P}_{jik}^m \tilde{M}_{jik}$ are expenditures by plant i on material input k . \tilde{P}_{jik}^m is the price index for material input k and plant i . $\tilde{\tau}_{jik}$ is the import tariff for material input k and plant i . λ_{ji} is a plant fixed effect which absorbs changes in both the price index for the material input bundle as well changes in total plant spending on materials. Δ refers to long-differences between the pre-reform period (1989) and the post-reform period (1995-

1997).²⁸ We simplify our estimation by first averaging the long-differences for each plant between 1989-1995, 1989-1996 and 1989-1997 – we therefore only have a single observation for each plant-input.²⁹ ρ_m is the elasticity of domestic input prices with respect to import tariffs, and β_m is the estimate of $(1 - \theta^m)$: the elasticity of substitution between different categories of material inputs. For our baseline results, we use industry spending shares when constructing the price indices and tariff measures ($\tilde{\tau}_{jik} = \tilde{\tau}_{jk}$ and $\tilde{P}_{jik} = \tilde{P}_{ik}$). The main reason is that, by using industry ‘leave-one-out’ shares in the instrument, we avoid any mechanical correlation between our instrument and our dependent variable through 1989 plant spending shares.³⁰ The second reason is that we have a slightly larger sample size when using industry shares rather than plant shares.³¹ It is also important to note that our specification conditions on surviving plants. These tend to be larger and use more inputs than the typical Indian manufacturing plant.³² In addition, because our specification uses log-changes in spending shares and prices, we restrict our sample to material input categories which are used both before and after the reform. However, an advantage of estimating the elasticity of substitution across nine highly aggregated categories of material inputs is that there is relatively little input churning; only 11.6% of inputs reported in 1989 are not reported again in the post-reform period, and these inputs only account for a 3% share of spending on average.³³

Similarly, equation 3 provides the theoretical basis for the following 2SLS empirical specification:

$$\text{First stage: } \Delta \ln \left(\frac{\tilde{P}_{ji}^m}{\tilde{P}_{ji}^z} \right) = \lambda_z + \rho \Delta \ln(1 + \tilde{\tau}_{ji}) + \eta_{ji} \quad (6)$$

$$\text{Second stage: } \Delta \ln \left(\frac{\tilde{P}_{ji}^m \tilde{M}_{ji}}{\tilde{P}_{ji}^z \tilde{Z}_{ji}} \right) = \lambda_z + \beta \Delta \ln \left(\frac{\tilde{P}_{ji}^m}{\tilde{P}_{ji}^z} \right) + \epsilon_{ji} \quad (7)$$

$z \in \{e, s\}$ and $Z \in \{E, S\}$. $\left(\frac{\tilde{P}_{ji}^m \tilde{M}_{ji}}{\tilde{P}_{ji}^z \tilde{Z}_{ji}} \right)$ is the expenditure of plant i on material inputs

²⁸We don’t include the years 1993 and 1994 in order to focus only long-differences. We also find weak and imprecise relationship between import tariffs and domestic prices when we restrict our analysis to changes between 1989 and 1993/1994 (results available upon request).

²⁹This has the additional benefit of averaging out measurement error. For expenditure shares, we take the log-change of the average expenditure shares rather than the average of the log-changes, as this incorporates the extensive margin of input-use (we find similar results in both cases).

³⁰Our estimation is closely related to the Bartik instruments approach, in which ‘leave-one-out’ shares are standard (see Goldsmith-Pinkham et al. (2017)).

³¹Because our WPI-ASICC concordance does not cover the full set of material inputs used by Indian plants, there are plant-inputs for which we can’t construct a plant-specific price index. However, we can still construct an industry-specific price index for these plant-inputs. These plant-inputs drop out of the specification with plant spending shares, but not of the specification with industry spending shares.

³²For more details see Appendix A4. and Table 14.

³³More details on the extensive margin of input use are available in Table 16.

relative to energy (or service) inputs. $\left(\frac{\tilde{P}_{ji}^m}{\tilde{P}_{ji}^z}\right)$ is the price index for material inputs relative to energy (or service) inputs for plant i . $\tilde{\tau}_{ji}$ is the import tariff on material inputs for plant i . λ_z is an intermediate input category fixed effect. Δ refers to long-differences between the pre-reform period (1989) and the post-reform period 1995-1996.³⁴ ρ is the elasticity of relative domestic input prices with respect to import tariffs. β is an estimate of $(1 - \theta)$: the elasticity of substitution between material, energy and service inputs. In our theoretical model there is a common elasticity between materials, energy and services. As a baseline specification we therefore pool together equations 6 and 7 for $Z = E$ and $Z = S$. For the same reasons we previously described, in our baseline specification we use industry spending shares when constructing the price indices and tariff measures ($\tilde{\tau}_{ji} = \tilde{\tau}_j$ and $\left(\frac{\tilde{P}_{ji}^m}{\tilde{P}_{ji}^z}\right) = \left(\frac{\tilde{P}_j^m}{\tilde{P}_j^z}\right)$).

4.2. Identification Strategy

4.2.1. OLS Bias

In order to evaluate the validity of our IV strategy it is helpful to review the sources of bias in the OLS estimation of the elasticity of substitution θ_m . ϵ_{jik} is the structural error term from Equation 5. In slight abuse of notation, all of the following variables are implicitly residualized on the plant fixed effects λ_{ji} :

$$\epsilon_{jik} = \Delta \ln \left(\frac{\tilde{P}_{jik}^m \tilde{M}_{jik}}{P_{jik}^m M_{jik}} \right) - (1 - \theta_m) \Delta \ln \left(\frac{\tilde{P}_{jik}^m}{P_{jik}^m} \right) + \theta_m \Delta \ln(\pi_{jik})$$

The structural error term includes: measurement error in expenditure shares, measurement error in prices and technological demand shifts. The bias in the OLS estimate can therefore be decomposed into the following three terms:

$$\begin{aligned} (\hat{\theta}_m^{\text{OLS}} - \theta_m) \text{Var}[\Delta \ln(\tilde{P}_{jik})] &= -\text{Cov} \left[\Delta \ln \left(\frac{\tilde{P}_{jik}^m \tilde{M}_{jik}}{P_{jik}^m M_{jik}} \right), \Delta \ln(\tilde{P}_{jik}) \right] \\ &\quad + (1 - \theta_m) \text{Cov} \left[\Delta \ln \left(\frac{\tilde{P}_{jik}^m}{P_{jik}^m} \right), \Delta \ln(\tilde{P}_{jik}) \right] \\ &\quad - \theta_m \text{Cov} \left[\Delta \ln(\pi_{jik}), \Delta \ln(\tilde{P}_{jik}) \right] \end{aligned} \quad (8)$$

³⁴Because of changes in the reporting of energy and services in the 1997 ASI survey we restrict our estimation of θ to the years 1989, 1995 and 1996.

The first covariance term captures the covariance of measurement error in expenditure shares (the dependent variable) with prices (the independent variable). This is more likely to be a source of bias when using plant spending shares to construct $\Delta \ln(\tilde{P}_{jik})$ than when using industry spending shares.³⁵ The second covariance term captures the bias induced by measurement error in the independent variable: i.e. attenuation bias. To the extent that measurement error in prices is classical, this will tend to bias OLS estimates of θ_m towards 1. The third covariance term captures simultaneity bias; the relationship between demand shocks $\Delta \ln(\pi_{jik})$ and changes in prices $\Delta \ln(\tilde{P}_{jik})$. The concern is that technological shifts in demand for a particular material input could be related to changes in the prices for those inputs. For example, if shirt manufacturers purchase more chemical-intensive capital equipment, the increase in demand for chemical inputs could lead to an increase in the prices charged by chemical input producers (this would occur provided that supply curves are upward sloping). Increases in expenditure shares will therefore be associated with increases in input prices. This positive covariance between $\Delta \ln(\pi_{jik})$ and $\Delta \ln(\tilde{P}_{jik})$ will lead to a downward bias in the OLS estimate of θ_m .

4.2.2. Import Tariffs as IV

Overview

Given the various sources of bias identified in Equation 8 we estimate the elasticities of substitution θ_m and θ using an instrumental variables strategy. We use Indian tariffs on imported inputs to instrument for domestic input prices. We focus on the period of India's trade liberalization (1989-1997) in order to reduce concerns regarding the endogeneity of tariff changes.

Historical Context

Following its independence in 1947 India's government imposed strict controls and restrictions on the manufacture of goods. This industrial policy involved licensing restrictions, small-scale reservations, FDI restrictions, high import tariffs and non-tariff barriers.³⁶ These restrictions started to be gradually relaxed during the 1980s, however India still remained a tightly regulated economy in 1990-1991, the last years before the major wave of reforms. The rise in the price of oil and drop in remittances following the first Gulf War triggered a balance of payments crisis for the Indian government in 1991, forcing it to turn to the IMF for assistance. This assistance was conditional on an adjustment program which involved major structural reforms. An important component of these reforms was

³⁵ Plant spending shares for sub-categories of materials do get used when constructing industry price indices for each category of material inputs. However, with a sufficient number of plants per industry, measurement error should average out.

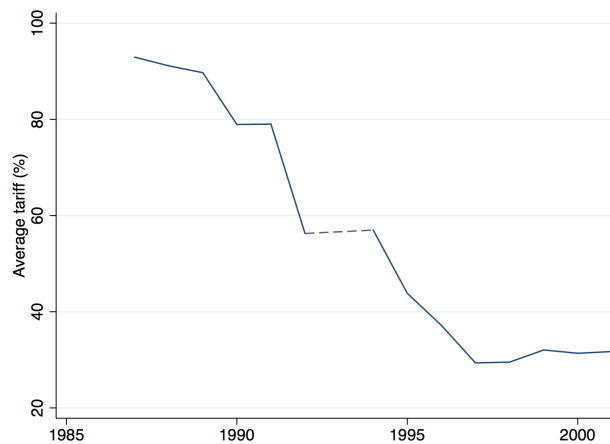
³⁶ See for example Sivadasan (2009) or Panagariya (2004).

trade liberalization. As discussed in [Topalova \(2010\)](#) and [Topalova and Khandelwal \(2011\)](#), because of the sudden and unexpected nature of the crisis, these reforms were pushed through rapidly and without much scope for industry lobbying.³⁷

Instrument Relevance

There are a number of features of India's trade liberalization that make import tariffs an appealing instrument to use in estimating medium to long-run elasticities of substitution. Firstly, as shown in [Figure 1](#) the decline in tariffs was both large and permanent. Between 1989 and 1997 Indian tariffs declined from 93% to 29%. From 1997 onwards import tariffs stayed relatively flat. The permanence of the tariff declines is important in that we might expect that firm responses to temporary price shocks could differ to their responses to permanent price shocks.³⁸ Secondly, the decline in import tariffs was highly heterogeneous across material inputs. Along with a reduction in average tariffs, one of the goals

Figure 1: Average Indian Tariffs Over Time



The figure plots the decline in average Indian tariffs (at the HS6 level) between 1988 and 2002. The data comes from [Topalova \(2010\)](#). 1993 is omitted because of concerns of measurement error (see [A5](#)).

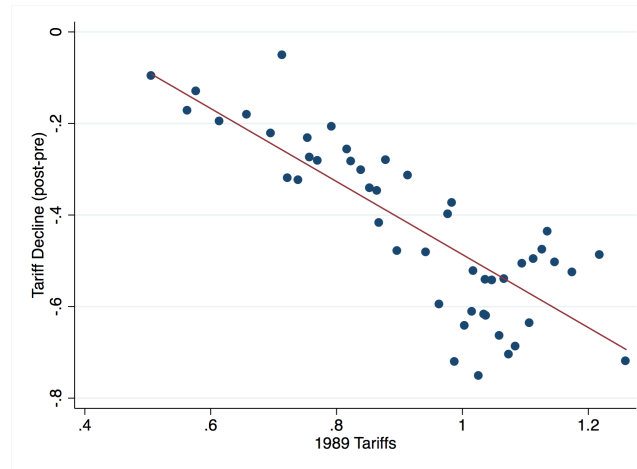
of India's trade liberalization was to compress the dispersion in tariffs across inputs. [Figure 2](#) plots the change in tariffs between 1989 and 1997 against the level of tariffs in 1989. It is clear that import tariffs were highly heterogeneous across inputs in 1989, and inputs with the highest initial tariffs experienced the largest tariff declines. This variation in tariff

³⁷Dr. Raja Chelliah, chairman of the Indian Tax Reforms Committee between 1991 and 1993 stated in a 2004 interview: 'When we started economic reforms in 1991, we concentrated on the most urgent things that anyhow had to be done, like delicensing, reform of the exchange control system, financial market reforms, and banking reforms. We didn't have the time to sit down and think exactly what kind of a development model we needed'.

³⁸For example, if there are fixed costs of changing a firm's input mix, firms may not adjust in response to temporary price shocks.

changes across inputs provides us with the variation to identify the elasticity of substitution between material inputs. Our estimation strategy relies on domestic input prices re-

Figure 2: Initial Tariffs vs Tariff Changes



The figure is a binned scatter plot of Indian tariffs in 1989 on the x-axis and the change in Indian tariffs between 1989 and 1997 on the y-axis. The tariffs measures are those that go into the estimation of θ_m ; they are therefore at the 1-digit material input category \times 4-digit industry level.

sponding to changes in import tariffs. In Figure 3 we plot a binned scatter plot of domestic price changes against import tariff changes. We estimate a strongly significant elasticity of domestic input prices with respect to import tariffs rate of 25.4%.³⁹ Why do domestic input prices respond to reductions in import tariffs for the same products? Our specification exploits the pro-competitive effects of tariff reductions – import competition forces Indian plants to reduce markups or improve their productivity (for example by reducing ‘X-inefficiencies’).⁴⁰

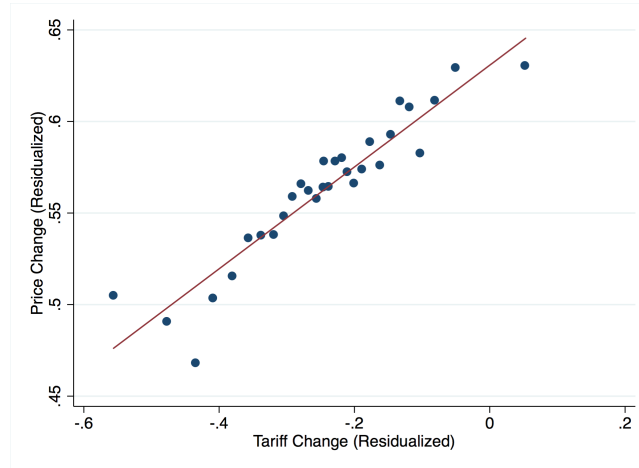
Exclusion Restriction

In order for the exclusion restriction to hold we also require that the tariff changes are

³⁹The standard error is 5.2%. De Loecker et al. (2016) document an elasticity of 13.6% between 1989 and 1997 using reported output prices in the firm-product level database *Prowess*. When we construct our tariff changes in level-changes as they do (rather than log-changes), we estimate a very similar elasticity of 15.7%. Using the same source of data Topalova (2010) documents a similar elasticity of tariff changes to price changes between 1987 and 2001 of 9.6% (the estimation is run as a panel regression rather than in long-differences).

⁴⁰An alternative approach would be to exploit the pass-through from import tariffs to domestic input prices through marginal cost reductions. However, De Loecker et al. (2016) find evidence that this pass-through was reduced because Indian plants raised their markups in response to falling marginal costs. We plan to explore this estimation approach in future versions of the paper.

Figure 3: First-Stage Relationship: Import Tariffs vs Domestic Prices



The figure is a binned scatter plot version of our first-stage regression, with changes in Indian tariffs on the x-axis and changes in domestic prices on the y-axis. Both variables are residualized on plant fixed-effects. The tariff and price measures are those that go into the estimation of θ_m ; they are therefore at the 1-digit material input category \times 4-digit industry level.

uncorrelated with the residual from Equation 5. We have that:

$$\begin{aligned}
 (\hat{\theta}_m^{IV} - \theta_m) \propto & -\text{Cov} \left[\Delta \ln \left(\frac{\tilde{P}_{jik}^m \tilde{M}_{jik}}{P_{jik}^m M_{jik}} \right), \Delta \ln(1 + \tilde{\tau}_{jik}) \right] \\
 & + (1 - \theta_m) \text{Cov} \left[\Delta \ln \left(\frac{\tilde{P}_{jik}^m}{P_{jik}^m} \right), \Delta \ln(1 + \tilde{\tau}_{jik}) \right] \\
 & - \theta_m \text{Cov} [\Delta \ln(\pi_{jik}), \Delta \ln(1 + \tilde{\tau}_{jik})]
 \end{aligned} \tag{9}$$

Concerns regarding technological pre-trends and the endogeneity of trade policy are captured by the third covariance term. A correlation between tariff changes and technological trends would introduce a bias into our estimation. A particular concern is that industries lobbied for tariff reductions on the inputs they planned on using more intensively in the future. Unfortunately, because the ‘detailed’ ASI surveys on plant-level input use are only available for one pre-reform year (1989), we can’t check for pre-trends in manufacturing intermediate input shares using the same data source. However, we expect that trends in the intermediate input shares of manufacturing plants would be reflected by trends in the size of sectors producing those inputs.⁴¹ We show in Table 17 that changes in tariffs between 1989 and 1995-97 are uncorrelated with the growth rate of output (real and nominal), labor and TFP of manufacturing industries between 1985 and 1988. We also show that

⁴¹If manufacturing plants were spending increasing amounts on chemical inputs between 1985 and 1988, we should expect to see the size of the chemicals industry growing over the same period.

wholesale price index changes between 1985 and 1988 are uncorrelated with tariff changes between 1989 and 1995-1997. Our results support evidence from [Topalova and Khandelwal \(2011\)](#) that the changes in import tariffs were unanticipated and not directed towards any particular industries.⁴² There were however a few exceptions to the ‘randomness’ of the decline in tariffs during the trade liberalization. The Indian government maintained full control of imports of oil-seeds, cereals and pulses, fertilizers and fuels throughout the trade liberalization.⁴³ We therefore drop these inputs from our estimation.

Another concern regarding the validity of our instrument is that our measures of tariff changes could be correlated with measurement error in the plant or industry material input price indices. This could arise for plants that directly import inputs from abroad because our price indices only reflect changes in domestic input prices. If the effect of tariff reductions on imported input prices is larger than on domestic input prices, then the decline in the domestic price index will understate the decline in the true price index precisely when tariffs fall more. Given this concern, we check robustness of all our results to dropping imported plant-input observations. Another way that a correlation between measurement error in the price index changes and the tariff changes could occur is if our measures of domestic input prices do not appropriately capture input quality changes. An extensive trade literature has shown that declines in import tariffs are associated with quality upgrading among domestic firms. As previously discussed, this is an important reason for not using unit value measures of input prices in our estimation. By using the Indian wholesale price index, which in principle should capture changes in input quality, we hope to allay concerns of quality bias.

5. Elasticity Estimates

5.1. Baseline Results

5.1.1. Estimates of θ_m

Our baseline estimates of the elasticity of substitution between material inputs (θ_m), based on Equations 4 and 5, are shown in Table 2. Our sample contains 21,673 plant-input observations and 8,420 plants. Our instrument varies at the industry-input level and so we cluster standard errors at the 4-digit industry-level. We estimate an elasticity of domestic

⁴²In addition to checking pre-trends, [Topalova and Khandelwal \(2011\)](#) show that 1989-1997 tariff changes are uncorrelated with other industry characteristics which might have been associated with lobbying power, such as size, productivity and capital intensity.

⁴³As discussed in [Panagariya \(2004\)](#) and [Topalova \(2010\)](#), this import ‘canalization’ was typically to protect poor agricultural producers of these products. In 1999 the U.S. filed a lawsuit against the Indian government through the WTO for continued quantitative restrictions on certain imports. The list of imported inputs that maintained quantitative restrictions is laid out there.

Table 2: Baseline estimates of θ_m

	First Stage $\Delta \ln(\tilde{P}_{jk}^m)$	OLS $\Delta \ln(\tilde{P}_{jk}^m \tilde{M}_{jik})$	IV $\Delta \ln(\tilde{P}_{jk}^m \tilde{M}_{jik})$
$\Delta \ln(1+\tilde{\tau}_{jk})$	0.254*** (0.052)		
$\Delta \ln(\tilde{P}_{jk})$		-0.226 (0.157)	-3.265*** (0.920)
Implied $\hat{\theta}_m$		1.23 [0.92,1.53]	4.27 [2.45,6.07]
Observations	21,673	21,673	21,673
Plant FEs	YES	YES	YES
# plants	8,420	8,420	8,420
F-stat	23.9	-	-

95% confidence intervals are in square brackets [] and standard errors are in curly brackets (). j = industry, i = plant, k = input. Standard errors are clustered at the 4-digit industry level. There are 335 4-digit NIC87 industry clusters. The 1% tails of expenditure share growth rates are trimmed.

input prices with respect to import tariffs of 25.4%. The first-stage is strong, with a standard error of 5.2% and an F-statistic of 23.4. Our OLS estimate of θ_m is 1.23 with a standard error of 0.16. Our IV estimate is 4.27 with a standard error 0.92. The 95% confidence interval is [2.45,6.07]. This provides strong evidence that the medium/long-run elasticity of substitution is significantly above 1. The bias in the OLS estimate of substitution also goes in the expected direction. As discussed previously, both attenuation bias and simultaneity bias should lead us to downward biased estimates of θ_m . In addition, our OLS estimates could be picking up both short-run fluctuations in prices as well as long-run fluctuations. To the extent that short-run fluctuations are an important source of variation and that short-run elasticities are close to 0, this might provide an additional source of downward bias in the OLS estimates.

5.1.2. Estimates of θ

Our baseline estimates of the elasticity of substitution between energy, material and service inputs (θ), based on Equations 6 and 7, are shown in Table 3. Our sample contains 16,640 plant-input pair observations and 8,434 plants.⁴⁴ Our instrument varies at the industry-input pair level and so we cluster standard errors at the 4-digit industry-level. We

⁴⁴The sample of plants is slightly larger as we do not need to restrict ourselves to plants that use multiple categories of material inputs.

Table 3: Baseline estimates of θ

	First Stage	OLS	IV
	$\Delta \ln \left(\frac{\tilde{P}_j^m}{\tilde{P}_j^z} \right)$	$\Delta \ln \left(\frac{\tilde{P}_{ji}^m \tilde{M}_{ji}}{\tilde{P}_{ji}^z \tilde{Z}_{ji}} \right)$	$\Delta \ln \left(\frac{\tilde{P}_{ji}^m \tilde{M}_{ji}}{\tilde{P}_{ji}^z \tilde{Z}_{ji}} \right)$
$\Delta \ln(1+\tau_j)$	0.414*** (0.102)		
$\Delta \ln \left(\frac{\tilde{P}_j^m}{\tilde{P}_j^z} \right)$		0.185 (0.251)	0.104 (0.600)
Implied $\hat{\theta}$		0.82 [0.32,1.31]	0.90 [-0.17,2.07]
Observations	16,640	16,640	16,640
# plants	8,434	8,434	8,434
<i>E/S</i> FEs	YES	YES	YES
F-stat	16.6	-	-

95% confidence intervals are in square brackets [] and standard errors are in curly brackets (). j = industry, i = plant, k = input. Standard errors are clustered at the 4-digit industry level. There are 335 4-digit NIC87 industry clusters. The .5% tails of expenditure share growth rates are trimmed.

estimate a pass-through rate of 41.4% from import tariffs to relative domestic input prices. Again the first-stage is relatively strong, with a standard error of 10.2% and an F-statistic of 16.6. Our OLS estimate of θ is 0.82 with a standard error of 0.25. Our IV estimate is very similar, with a point estimate of 0.90 and a standard error of 0.60. The 95% confidence interval is [-0.2,2.1]. Unfortunately, our empirical results do not allow us to pin down with any certainty if θ is below 1 or greater than 1. In this case, if θ is less than 1, attenuation bias and simultaneity bias could be pushing in opposite directions. The fact that we estimate a slightly higher elasticity with our IV would indicate that simultaneity bias is a more important source of bias than attenuation bias.⁴⁵

5.2. Robustness of θ_m Estimates

Our baseline empirical estimates are robust to a variety of checks shown in Table 4 and in the Appendix in Table 19 and Table 20. In Table 4 we show that our estimates are robust to using plant spending shares when constructing prices and the tariff measures.⁴⁶ We

⁴⁵It would also be possible for attenuation bias and simultaneity bias to be pushing in the same direction if θ is in fact greater than 1.

⁴⁶We use 1989 plant-specific spending shares when constructing the tariff instrument, and average plant spending shares when constructing Tornqvist prices.

also show that our restriction to domestic inputs does not have an important impact on our estimates. In Table 19 we allay concerns regarding outliers and measurement error by varying the extent of trimming/winsorizing of expenditure share changes, price changes and tariff changes. As discussed previously, government manipulation of import tariffs and non-tariff barriers was more likely for agricultural products which were produced by poorer rural Indian farmers. We therefore also re-run our estimation on the sample of non-primary food inputs and manufactured inputs. Our estimates remain similar in magnitude and significance. Another concern is that our results might be driven by inputs that make up only a small share of total plant costs. Our estimates are robust to setting a minimum value share threshold for the inputs used by plants, and to restricting the sample to only the main two inputs used by the plant. As discussed previously, we do not match all inputs reported in the 1989 'ASI Item Code' classification to the ASICC classification. We check that this doesn't impact our estimates by restricting the sample to plants for whom our concordance captures at least 90% or 99% of expenditures on materials in 1989. Our results remain robust and highly significant. As discussed in Section 4, our identification strategy exploits variation in tariffs, prices and expenditure shares across industries within inputs as well as across inputs. To check the sensitivity of our results to the presence of specific inputs in the estimation, we re-run our estimation dropping each input in turn. These results are shown in Table 20. Our first-stages remain strong and our point estimates are all significantly greater than 1. At the extremes, our estimate fall to 2.55 (0.58) when we drop 'Base Metals' and rise to 7.90 (2.3) when we drop 'Textiles'.

5.2.1. Discussion

Our estimates of the within-materials elasticity of substitution stand in stark contrast to estimates of the short-run elasticity of substitution between intermediate inputs. Boehm et al. (2016) and Atalay (2017) estimate short-run elasticities of substitution between intermediate inputs using U.S. sector-level and firm-level data respectively. Both estimate elasticities over time horizons of one year or less and find that intermediate inputs are close to Leontief. Our finding of an elasticity of substitution above 4 is considerably higher, especially given that it is estimated across 9 relatively aggregated categories of materials.⁴⁷ In the very short-run, plants may be unable to change suppliers or may have contracts in place preventing them from doing so. They may therefore not adjust to input price shocks, particularly if the shocks are temporary. The long-run response to (large) permanent price shocks may be quite different however. The existence of large dispersion in material input shares among plants in the same industry (as shown in Figure 7) suggests that there

⁴⁷It is natural to expect a lower degree of substitutability between more highly aggregated input categories: e.g. different types of wood are likely more substitutable than wood and plastics.

Table 4: Robustness of θ_m Estimates

Specification	First-Stage	OLS	Second Stage	# Obs	# Plants
Baseline	0.254*** (0.052)	-0.226 (0.157)	-3.265*** (0.920)	21,673	8,420
<i>Plant shares used to construct:</i>					
Prices	0.244*** (0.051)	-0.226 (0.205)	-3.503** (1.640)	19,535	7,476
Prices & Tariffs	0.221*** (0.048)	-0.185 (0.212)	-4.177** (1.787)	18,843	7,376
<i>Robustness to dropping imported inputs</i>					
Keep imported inputs	0.254*** (0.050)	-0.263 (0.160)	-3.490*** (0.957)	23,075	8,478
Drop importers	0.260*** (0.061)	-0.175 (0.169)	-2.912*** (0.977)	17,243	6,517

This table presents first-stage, OLS and second-stage results from the regressions shown in equations 4 and 5. The first row presents the baseline results as shown in Table 2. The second and third rows show robustness to using plant-specific spending shares (instead of industry spending shares) when constructing the input price and tariff measures. The fourth and fifth rows show robustness to keeping imported inputs in the sample, and to dropping any plant that reports importing at least one input. All regressions include plant fixed effects. Standard errors are clustered at industry-level and shown in brackets.

may be many possible technologies for the production of differentiated goods.⁴⁸ Plants may be able to invest in new capital equipment which changes the relative intensity with materials are used. They may also be able to do R&D or innovate, undertaking directed technical change to reduce their reliance on an input whose price has risen.⁴⁹ They may also be able to improve the management of inventories or reduce similar ‘X-inefficiencies’. This may particularly relevant in the Indian setting given the findings in Bloom et al. (2013) that large Indian textile plants wasted considerable amounts of materials. Plants may also switch to producing slightly different products within the same product category: e.g. 50% cotton shirts rather than 90% cotton.⁵⁰ In Section 7. and Appendix B1. we consider this alternative interpretation of our empirical findings. We show that, even if our model is misspecified and each product is produced using a Leontief production function (but plants substitute between products), our counterfactual results may not be particularly sensitive

⁴⁸Of course, at least some of this dispersion is likely due to measurement error (Bils et al. (2017)).

⁴⁹Making changes to the production process may also require time and involve fixed costs (e.g. new capital equipment, R&D). This is an additional reason that substitutability in the short-run is lower than in the long-run.

⁵⁰Our empirical results restrict to plants that stay within the same 4-digit NIC87 industry.

to this form of misspecification.⁵¹ Long-run elasticities of substitution can therefore be thought of capturing forms of directed technical change which may take time to implement.⁵² Uncovering the precise mechanisms underlying how these technological changes occur is beyond the scope of this paper however.

5.3. Simulations: Tornqvist vs. Alternative Price Indices

When constructing the price indices used in our estimation, we weight price changes at the lower levels of aggregation using average plant (or industry) spending shares. We thus construct Tornqvist price indices, which provide a second-order approximation to the change in the true price index for any value of the elasticity of substitution at the lower level of aggregation. However, this second order approximation may not perform well in practice. In particular, measurement error in spending shares, input-biased technological shocks and misspecification of the nesting structure could all be causes of concern. We check this by carrying out simulations and evaluating the performance of the Tornqvist price index compared to two other standard price indices; Laspeyres and Paasche.

We simulate tariff shocks and price changes for 90 inputs used by 1000 plants. In our baseline simulation, plants have a nested CES production function, where the 90 ‘lower-level’ inputs are equally divided into 9 ‘upper-level’ categories of inputs. The elasticity of substitution at the upper level of aggregation is 4, and at the lower level of aggregation is 10. Plants have heterogeneous input-biased technologies (weights in the CES production function), and therefore have heterogeneous spending shares. We randomly draw shocks to the ‘import tariffs’ on each input - these are heterogeneous across inputs but common across plants.⁵³ The price change of each input is then a function of the import tariff shock and a random noise component.⁵⁴ Like tariffs, prices are heterogeneous across inputs but common across plants. We calculate the new plant spending shares, construct the Tornqvist, Laspeyres and Paasche price indices, and carry out the OLS and IV estimation of the ‘upper-level’ elasticity of substitution. The average bias and the standard deviation of the estimates across 20 simulations are shown in the first two rows of Table 5. We find that the average bias is 0.17 for the OLS, and 0.07 for the IV, and the dispersion of the estimates

⁵¹The sensitivity of our results depends on the size of the shocks considered, the number of varieties that plant substitute between and the degree of heterogeneity in the production technologies for each product.

⁵²Labor and capital augmenting technical change has more often been the focus of the directed technical change literature (e.g. [Acemoglu \(2003\)](#))

⁵³The import tariff shocks are assumed to be log-normal with a standard deviation of 0.20, matching the dispersion in the data.

⁵⁴We construct log-price changes as 0.35 times the log-tariff change plus a random noise component. We are therefore assuming an elasticity of domestic input prices with respect to import tariffs of 35%, which is broadly in line with what we estimate in the data (half way between the first-stage estimate in Tables 2 and 3, and allowing for a little bit of attenuation due to measurement error in import tariffs). The noise term is distributed log-normal with a standard deviation of 0.187. This implies that the dispersion in input price changes is approximately 0.20, as it is in the data.

is (0.06) and (0.19) respectively.⁵⁵ The average bias and the dispersion of the estimates are much larger when we use the Laspeyres and Paasche price indices – the second-order Tornqvist approximation performs comparatively well. We also consider three more simulations. In the ‘Technology Shocks’ simulation we add random shocks to the input-biased technologies; spending shares are therefore partly changing independently of prices. In the ‘Meas. Err in Shares’ simulation we add i.i.d. measurement error to the ‘lower level’ plant spending shares which get used to construct the price indices. Finally, in the ‘Mis-specified Nests’ simulation we estimate the elasticity of substitution across the ‘upper-level’ inputs as before, despite the true model not having any nesting structure and the true elasticity of substitution being equal to 10. In all cases we find lower average bias and more precise estimates when using Tornqvist price indices.

6. Quantitative Model

6.1. Overview

In order to evaluate the importance of intermediate input substitution for economic development policies, we embed the model of plant-level production laid out in Section 2. into a general equilibrium framework. In particular, we consider a static open economy consisting of multiple sectors. In each sector, firms produce differentiated and tradable varieties using labor and intermediate inputs. There is an inelastic supply of labor which is immobile across borders; the wage therefore clears the domestic labor market. Import (and export) prices are taken as given by all domestic agents, and we impose trade balance. The demand side is kept very simple - a representative consumer has preferences over domestic and imported varieties of consumption goods produced in all sectors. Instead of specifying preferences for each variety, we use the standard trick of aggregating varieties within a sector into a sectoral good, and aggregating sectoral goods into a single aggregate consumption good. Labor and intermediates are the only inputs in production; we do not model the dynamics of capital accumulation.⁵⁶ We build on the canonical multi-sector general equilibrium model of Long and Plosser (1983), incorporating heterogeneous firms with non-unitary production elasticities.⁵⁷

⁵⁵Note that the measurement error from the Tornqvist approximation is not classical measurement error, and therefore there is no reason to expect attenuation bias in the OLS estimate.

⁵⁶Adding capital should not affect the main insights from our counterfactual exercises – that the aggregate productivity gains from shocks to individual sectors are significantly amplified through intermediate input substitution. However, we plan on incorporating capital accumulation in future versions of the paper.

⁵⁷Other papers to incorporate non-unitary elasticities include Jones (2011), Atalay (2017) and Baqaee and Farhi (2017).

Table 5: Simulations: Tornqvist vs. Laspeyres vs. Paasche Price Indices

	OLS			IV		
	Tornqvist	Laspeyres	Paasche	Tornqvist	Laspeyres	Paasche
<i>Baseline</i>						
Average $\hat{\theta}^m$	4.17	3.4	3.55	4.07	3.62	5.86
Standard deviation	0.06	0.21	0.14	0.19	0.74	2.63
<i>Technology Shocks</i>						
Average $\hat{\theta}^m$	4.15	3.41	3.55	3.92	3.3	7.01
Standard deviation	0.04	0.17	0.09	0.41	0.72	6.7
<i>Meas. Error in Shares</i>						
Average $\hat{\theta}^m$	4.18	3.5	3.51	4.09	3.74	5.08
Standard deviation	0.05	0.24	0.13	0.13	0.55	1.14
<i>Misspecified Nests</i>						
<i>True $\hat{\theta}^m = 10$</i>						
Average $\hat{\theta}^m$	10.51	8.37	8.68	10.13	8.71	15.14
Standard deviation	0.15	0.55	0.31	0.49	1.75	7.56

Notes: The numbers in the table are the average and standard deviation of the elasticity estimates over 20 simulations. The columns correspond to OLS or IV estimates, using Tornqvist, Laspeyres or Paasche price indices as part of the estimation. The steps involved for the Baseline simulations are described in the text. For the 'Technology Shocks' simulation we multiply the input-biased CES technologies by i.i.d. shocks drawn from a lognormal distribution with a standard deviation of 0.05. For the 'Meas. Error in Shares' simulation we multiply the 'lower-level' plant spending shares by i.i.d. shocks drawn from a lognormal distribution with a standard deviation of 0.05. For the 'Misspecified Nests' simulation, the true production function isn't nested, and there is a constant elasticity of substitution across all 90 inputs equal to 10.

6.2. Production

Heterogenous Firms

The economy consists of J sectors, which are classified into 3 broad types: energy, materials and services. There are J^e energy industries, J^m materials industries and J^s services industries. Each industry j is comprised of an exogenous number N_j of firms. We nest the firm production function from Section 2. directly into our quantitative model; firm i in sector j produces a variety Q_{ji} using labor and intermediates inputs according to the

following nested CES production function:

$$\begin{aligned}
 Q_{ji} &= A_{ji} \left(\gamma_{ji} L_{ji}^{\frac{\varepsilon-1}{\varepsilon}} + (1 - \gamma_{ji}) X_{ji}^{\frac{\varepsilon-1}{\varepsilon}} \right)^{\frac{\varepsilon}{\varepsilon-1}} \\
 X_{ji} &= \left[\pi_{ji}^e E_{ji}^{\frac{\theta-1}{\theta}} + \pi_{ji}^m M_i^{\frac{\theta-1}{\theta}} + \pi_i^s S_{ji}^{\frac{\theta-1}{\theta}} \right]^{\frac{\theta}{\theta-1}} \\
 Z_{ji} &= \left[\sum_{k=1}^{J^z} \pi_{jik}^z Z_{jik}^{\frac{\theta^z-1}{\theta^z}} \right]^{\frac{\theta^z}{\theta^z-1}} \quad \text{where } Z \in \{E, M, S\}
 \end{aligned}$$

As before, ε , θ and θ_z are the respective elasticities of substitution for each input bundle. We normalize the technological shifters to sum to 1 within each nest: $\pi_{ji}^e + \pi_{ji}^m + \pi_{ji}^s = 1$ and $\sum_{k=1}^{J^z} \pi_{jik}^z = 1$. We make one new structural assumption; the input bundle Z_{jik} is itself a CES bundle of domestic and imported inputs:

$$Z_{jik} = \left[\delta_{jk}^z (Z_{jik}^D)^{\frac{\eta-1}{\eta}} + (1 - \delta_{jk}^z) (Z_{jik}^I)^{\frac{\eta-1}{\eta}} \right]^{\frac{\eta}{\eta-1}}$$

We restrict firms in the same sector to have identical import shares: δ_{jk}^z doesn't vary across i .⁵⁸ Firms take input prices and their demand curve as given when maximizing profits Π_{ji} . In addition, firms face idiosyncratic 'revenue distortions' τ_{ji} :

$$\Pi_{ji} = \max (1 - \tau_{ji}) P_{ji} Q_{ji} - w L_{ji} - \sum_{\{z,k\}} P_{z,k}^D Z_{jik}^D - \sum_{\{z,k\}} P_{z,k}^I Z_{jik}^I$$

The revenue distortions are a tractable way of capturing anything that further distorts the optimal size of the firm: e.g. heterogeneous markups, implicit or explicit taxes and subsidies, or size regulations. These revenue distortions create a misallocation of inputs both within and across sectors, and are the only source of inefficiency in this economy.⁵⁹

Sectoral Output

The varieties produced by all firms in sector j are combined into a sectoral good by a perfectly competitive representative firm. In particular, this firm produces sectoral output Q_j according to the following CES aggregator:

⁵⁸Recent papers such as [Blaum et al. \(2016\)](#) and [Tintelnot et al. \(2017\)](#) have shown that heterogeneity in import shares is both prevalent across French and Belgian firms, as well as quantitatively important for evaluating the gains from trade. We will incorporate this dimension of heterogeneity in future versions of the paper.

⁵⁹[Restuccia and Rogerson \(2008\)](#) and [Hsieh and Klenow \(2009\)](#) are seminal papers in the literature on misallocation of inputs across plants. [Leal \(2015\)](#) analyzes misallocation across sectors in Mexico.

$$Q_j = \left(\sum_{i=1}^{N_j} Q_{ji}^{\frac{\mu-1}{\mu}} \right)^{\frac{\mu}{\mu-1}}$$

μ denotes the elasticity of substitution across firms within a sector. Cost-minimization by the sectoral good producer and the assumption of perfect competition imply that the demand curve faced by firm i in sector j is given by $P_{ji} = P_j Q_j^{\frac{1}{\mu}} Q_{ji}^{-\frac{1}{\mu}}$, where $P_j = \left(\sum_{i=1}^{N_j} P_{ji}^{1-\mu} \right)^{\frac{1}{1-\mu}}$.

Sectoral output Q_j is either used as an intermediate input by a firm in one of the J sectors, or is used as an input into final consumption.

Aggregate Consumption Good

As with sectoral goods, the aggregate consumption good is produced by a perfectly competitive final good producer. They combine domestic and imported consumption goods from each sector j using a nested CES production function. We impose the same nesting structure on the consumption side as we do on the production side. The first nest is over energy, materials and services consumption bundles:

$$Y = \left[\omega^e (E^c)^{\frac{\sigma-1}{\sigma}} + \omega^m (M^c)^{\frac{\sigma-1}{\sigma}} + \omega^s (S^c)^{\frac{\sigma-1}{\sigma}} \right]^{\frac{\sigma}{\sigma-1}}$$

The second nest is over goods coming from different sectors within energy/materials/services:

$$Z^c = \left[\sum_{k=1}^{J^z} \omega_k^z (Z_k^c)^{\frac{\sigma_z-1}{\sigma_z}} \right]^{\frac{\sigma_z}{\sigma_z-1}} \quad \text{where } Z \in \{E, M, S\}$$

The third nest is over domestic and imported sectoral consumption goods:

$$Z_k^c = \left[\delta_{c,k}^z (Z_k^{c,D})^{\frac{\eta_c-1}{\eta_c}} + (1 - \delta_{c,k}^z) (Z_k^{c,I})^{\frac{\eta_c-1}{\eta_c}} \right]^{\frac{\eta_c}{\eta_c-1}}$$

σ , σ_z and η_c are the consumption-side elasticities of substitution. We normalize the preference shifters to sum to 1 within each nest: $\omega^e + \omega^m + \omega^s = 1$ and $\sum_{k=1}^{J^z} \omega_k^z = 1$. The final good producer minimizes costs, taking domestic input prices ($P_{z,k}^D$) and imported input prices ($P_{z,k}^I$) as given.⁶⁰ We normalize the price of the aggregate consumption good to 1.

⁶⁰Where $z \in \{e, m, s\}$.

6.3. Consumption

There is a representative agent who supplies a fixed amount of labor, L , and derives utility from consuming the aggregate consumption good Y . Since this is a static environment, the representative agent simply maximizes their utility (C) subject to their budget constraint (B). The budget constraint includes their labor income, firm profits and revenue from distortions.

$$B = wL + \sum_{j=1}^J \sum_{i=1}^{N_j} \Pi_{ji} + \sum_{j=1}^J \sum_{i=1}^{N_j} \tau_{ji} P_{ji} Q_{ji}$$

6.4. Equilibrium

Sectoral output Q_j can either be used by firms as an intermediate input or can be used to produce the aggregate consumption good. Denoting by Q_k^z output from (material/energy/services) industry k , market clearing implies that:

$$Q_k^z = \sum_{j=1}^J \sum_{i=1}^{N_j} Z_{jik}^D + Z_k^{c,D}$$

Import prices are exogenous and we impose trade balance through exports of the aggregate consumption good:

$$\underbrace{\widehat{Y} - C}_{\text{Exports}} = \underbrace{\sum_{z \in \{e,m,s\}} \sum_{k=1}^{J_z} P_{z,k}^I Z_{jik}^{c,I}}_{\text{consumption}} + \underbrace{\sum_{j=1}^J \sum_{i=1}^{N_j} \sum_{z \in \{e,m,s\}} \sum_{k=1}^{J_z} P_{z,k}^I Z_{jik}^I}_{\text{intermediate inputs}} \quad \text{Imports}$$

We can now define a competitive equilibrium. Given a set of productivities $\{A_{ji}\}$, production technologies $\{\varepsilon, \theta, \{\theta^z\}, \eta, \{\gamma_{ji}\}, \{\pi_{ji}^z\}, \{\pi_{jik}^z\}, \{\delta_{jk}^z\}\}$, distortions $\{\tau_{ji}\}$, preferences $\{\sigma, \{\sigma^z\}, \eta_c, \{\omega^z\}, \{\omega_k^z\}\}$ and import prices $\{P_j^I\}$, an equilibrium is a set of, prices $\{w, \{P_j^D\}\}$ and quantities $\{\{L_{si}\}, \{Z_{jik}^I\}, \{Z_{jik}^D\}, \{Z_{jik}^{c,D}\}, \{Z_{jik}^{c,I}\}\}$ such that 1) the representative agent optimizes subject to their budget constraint 2) firms maximize profits 3) output markets clear 4) the labor market clears 5) the aggregate budget constraint holds 6) trade is balanced.

7. Calibration and Counterfactuals

7.1. Calibration

Data

We calibrate our model to match moments from both micro data and sectoral data for the Indian economy. Since the ASI micro data covers only manufacturing, we combine this with sectoral data for the whole economy from the World Input-Output Database (WIOD). The WIOD is a database of input-output flows between 35 2-digit NACE sectors in 40 countries, including India and the U.S. The years covered are 1995 to 2009. Domestic and imported intermediate inputs are reported separately.⁶¹ Consumption of domestic and imported goods from each sector are also reported. We use the Socio-Economic Accounts (SEA) to obtain measures of labor, labor compensation and the capital stock for each sector. Table 21 shows our final list of 29 sectors.⁶²

Elasticities

In Section 5, we estimated θ^m and θ .⁶³ In our baseline calibration we assume that the elasticities of substitution within energy and within services are equal to the elasticity of substitution within materials; $\theta^e = \theta^s = \theta^m$. For the remaining elasticities in the model, we choose existing medium/long-run estimates in the literature. These are shown in Table 6. The most important of these for our counterfactual exercises are the elasticities of substitution between consumption goods. As with the elasticities of substitution between intermediate inputs, these play an important role in amplifying or dampening the aggregate impact of productivity shocks in one sector of the economy.⁶⁴ We use estimates from [Hobijn and Nechio \(2017\)](#), who exploit changes in European VAT rates to estimate long-run aggregate elasticities of substitution across consumption goods at different levels of sectoral aggregation.⁶⁵ We use estimates of the elasticities of substitution between domestic and imported intermediate inputs/consumption goods from [Blaum et al. \(2016\)](#) and [Feenstra et al. \(2014\)](#) respectively.⁶⁶ Our estimate of the elasticity of substitution between

⁶¹ See [Timmer et al. \(2015\)](#). The data can be downloaded at the following link: <http://www.wiod.org/home>. It is worth noting that Indian I-O tables do not separately report expenditure on imports from expenditure on domestic intermediates by using sector. Import shares are therefore imputed for each using sector according to the methodology outlined in [Timmer et al. \(2015\)](#).

⁶² We drop the sectors 'Government' and 'Households with Employed Persons'. We also aggregate 13 manufacturing sectors into 9 sectors that more closely match the ASIC classification of material inputs. Our final list contains 11 'Materials' sectors, 2 'Energy' sectors and 16 'Services' sectors.

⁶³ It is worth noting that, while our estimation was only for Indian manufacturing plants, our model imposes that these production elasticities are the same in all sectors.

⁶⁴ Because consumption-side elasticities directly feed into aggregate consumption, they play an even larger quantitative role than production-side elasticities.

⁶⁵ We use their point estimate at the Division level (10 categories) for the elasticity of substitution between energy, materials and services, and their point estimate at the Group level (36 categories) for the elasticities of substitution within energy, materials and services.

⁶⁶ [Blaum et al. \(2016\)](#) use an instrumental variables strategy, treating changes in world export supply as an exogenous shock to French firms. [Feenstra et al. \(2014\)](#) use a GMM estimator based on [Feenstra \(1994\)](#) to

intermediate inputs and value-added comes from [Oberfield and Raval \(2014\)](#), however we plan on estimating this elasticity directly for Indian plants in future versions of the paper. The elasticity of substitution across varieties μ determines plant markups. We therefore set this equal to 3.94 to match the median markup in Indian manufacturing estimated in [De Loecker et al. \(2016\)](#).

Table 6: Elasticities in Baseline Calibration

Elasticity	Value	Description	Paper	Country
σ	1.0	consumption (upper)	Hobijn and Nechio (2017)	Europe
$\sigma_e = \sigma_m = \sigma_s$	2.6	consumption (lower)	Hobijn and Nechio (2017)	Europe
η	2.4	domestic & imported (intermediates)	Blaum et al. (2016)	France
η_c	2.0	domestic & imported (consumption)	Feenstra et al. (2014)	U.S.
ε	0.8	intermediates & (K,L)	Oberfield and Raval (2014)	U.S.
μ	3.9	across plants	De Loecker et al. (2016)	India

Consumer Preferences and Production Technologies

Given the consumption-side elasticities and WIOD data on Indian aggregate consumption shares, we can back out all the remaining model parameters governing consumer preferences.⁶⁷ We set the number of plants in every sector (N_j) equal to 300. We infer all plant-specific parameters from the market shares and input cost shares of a random sample of plants from the corresponding sector in the ASI.⁶⁸ ⁶⁹ However, we first adjust the plant cost shares so that, when aggregated, the ASI sectoral input cost shares match those in the WIOD.⁷⁰ Within-sector dispersion in revenue distortions (τ_{ji}) is inferred from dispersion in

correct for biases.

⁶⁷The remaining consumption-side parameters are the CES preference shifters: ω^z , ω_k^z and $\delta_{c,k}^z$. Sectoral good prices are also required to back out these parameters, but these can be normalized to 1 without loss of generality as this is simply a normalization of units.

⁶⁸300 plants roughly corresponds to a 10% sample of plants from each manufacturing sector in the ASI. We do not use the full sample for computational reasons: the time required to solve the model increases with the number of plants.

⁶⁹For non-manufacturing sectors, we draw plants from a random manufacturing sector in the ASI. This is because we do not have micro data outside of manufacturing. Our underlying assumption is that the joint distributions of distortions, market shares and input cost shares look similar inside and outside of manufacturing.

⁷⁰It is of course important to adjust the input cost shares for ASI plants that get drawn into non-manufacturing sectors. To keep things consistent, we also do this for plants drawn into manufacturing sectors.

plant profit shares (revenues/costs). We incorporate across-sector dispersion in revenue distortions by using sector-specific markup estimates from De Loecker et al. (2016). The level of the revenue distortions in each sector is adjusted to match the estimated markup in that sector.⁷¹ An important caveat in this calibration is that we only match micro data moments for the *formal* Indian manufacturing sector, however the *informal* sector is large in India. In future versions of the paper we will incorporate micro data moments for informal manufacturing plants from the Survey of Unorganized Manufactures (SUM).

7.2. Model Fit

We calibrate our model to match data from the 1995 ASI and WIOD, as this is the earliest year for which both are available. Our main counterfactual exercises involve evaluating the long-run aggregate impact of large shocks to sectoral TFP. An appropriate way of evaluating the ‘goodness of fit’ of our model is therefore to compare our model predictions from feeding in the observed 10-year changes in sectoral TFP and average sectoral distortions between 1995 and 2005 with the observed changes in the data. However, it is worth noting that our model is exactly identified – i.e. we can perfectly match the sector-level and plant-level moments in each year of the ASI/WIOD. For this goodness of fit test, we therefore hold all other parameters at their 1995 calibrated values: preferences, number of plants, plant production parameters (except for productivity and distortions) and import prices. We construct 10-year TFP growth rates from the WIOD as follows:

$$\Delta TFP_s = \Delta Q_s - \bar{\gamma}_s(\bar{\alpha}_s \Delta L_s + (1 - \bar{\alpha}_s) \Delta K_s) - (1 - \bar{\gamma}_s) \sum_{Z \in \{E, M, S\}} \sum_k \bar{\pi}_k^z \Delta Z_{sk}$$

ΔQ_s , ΔL_s , ΔK_s , ΔZ_{sk} are the 10-year growth rates of sectoral output (deflated), labor, capital (deflated) and intermediate inputs (deflated). γ_s , α_s and $\bar{\pi}_k^z$ are average cost shares.⁷² We infer the change in average sectoral distortions from the 10-year change in the ratio of revenues to total costs in each WIOD sector.⁷³ We introduce these shocks into the model by proportionately scaling plant-level productivities (A_{ji}), as well as plant-level revenue to cost ratios $\left(\frac{1}{1 - \tau_{ji}}\right)$, by the same sector-specific factor. The average 10-year sectoral TFP growth rate between 1995 and 2005 is 16.5% (4.2% in manufacturing) and the standard deviation is 30% (12.8% in manufacturing); there is considerable dispersion in productivity growth rates across sectors. Given our focus in this paper is on inter-

⁷¹De Loecker et al. (2016) sectoral markup estimates are only within manufacturing. We therefore assume that there is no dispersion in average sectoral distortions outside of manufacturing (median $\tau_{ji} = 0$).

⁷²Sector-specific deflators are used to deflate sales, intermediate inputs and capital. Cost shares are averages of the initial year and end year. We assume a rental rate of return of 20% on the capital stock when constructing the cost share of capital.

⁷³Among other interpretations, changes in revenues / costs could reflect time-varying markups.

mediate input substitution, we do our goodness of fit test under three different calibrations: a first ‘Complements’ calibration in which intermediate inputs are close to Leontief ($\theta = \theta^e = \theta^m = \theta^s = 0.1$), a second ‘Cobb-Douglas’ calibration in which intermediate inputs are Cobb-Douglas ($\theta = \theta^e = \theta^m = \theta^s = 1$) and a third ‘Substitutes’ calibration with our estimated elasticities ($\theta = 1, \theta^e = \theta^m = \theta^s = 4.27$). We evaluate the model fit by calculating the correlations between the 10-year growth rates of the following variables between the model and the data: sectoral sales shares, sectoral output prices, sectoral employment, sectoral spending on intermediates, sectoral shares of aggregate consumption and sectoral shares of aggregate intermediate spending. These results are shown in Table 7. The correlations between changes in the model and data are generally low, indicating

Table 7: Correlation between Changes in Model and Changes in Data

	Complements ($\theta = \theta^z = 0.1$)	Cobb-Douglas ($\theta = \theta^z = 1$)	Substitutes ($\theta = 1, \theta^z = 4.27$)
Sectoral Sales	0.048	0.124	0.152
Sectoral Price	0.524	0.524	0.519
Sectoral Employment	0.016	-0.039	-0.114
Sectoral Intermediate Expenditures	0.249	0.270	0.262
Share of Aggregate Consumption	-0.059	-0.073	-0.118
Share of Aggregate Intermediates	-0.600	-0.282	0.380

Notes: The results in the table contrast the the % gains predicted by our model for various counterfactuals described in the leftmost column. $\theta_z = 1$ is used as a stand in for $\theta_e = \theta_m = \theta_s = 1$, and similarly for $\theta_z = 4.27$.

that changes over time in consumer preferences, number of plants, relative plant distortions, production technologies and import prices are important in shaping the relative size of sectors in the Indian economy.⁷⁴ A positive is that the calibration with our estimated elasticities (Substitutes) has a much higher correlation between model and data for the variable which captures the key mechanism in this paper; the sectoral share of of aggregate intermediate spending. This correlation is 0.38 with our baseline calibration, but is negative in both the Cobb-Douglas calibration (-0.28) and the Complements calibration (-0.60).⁷⁵ Our exercise highlights the fact that changes in dimensions of the Indian econ-

⁷⁴Measurement error in the WIOD data could also worsen our model fit.

⁷⁵The results are similar if we calculate the (pooled) correlation between shares of intermediate spending in each sector. The variables for which the model performs the least well are sectoral employment and shares of aggregate consumption. The fact that the model fit is worse for sectoral employment than for sectoral intermediate expenditures may be an indication that frictions to labor reallocation in India are important even over a 10-year horizon. Employment may also not be the best measure of labor inputs – hours worked or sector-specific human capital may also be changing over time. The poor model fit for aggregate consumption shares could be an indication that our consumption elasticities are inappropriate for the Indian economy, or

omy other than average sectoral TFP and distortions are also crucial in shaping the relative size of sectors. Nonetheless, while a richer model may be required in order to make accurate forecasts of the exact structure of the Indian economy, we can still obtain insights into the aggregate importance of intermediate input substitution by evaluating the impact of changes in average sectoral TFP in this more stylized model.

7.3. Counterfactuals: ‘Big Push’ vs ‘Superstars’

Impact of Sectoral TFP Increases

We use our model, calibrated to the Indian ASI and WIOD for the year 1995, to evaluate the impact of an increase in average plant productivity (A_{ji}) in a *single sector* of the economy. Our baseline counterfactual involves a 50% increase in average plant TFP. While this is a large increase in the relative TFP of one sector, it is not in excess of measured 10-year sectoral TFP growth rates for India in the WIOD; the average TFP growth rate between 1995 and 2005 is 16.5% and the standard deviation is 30%.⁷⁶ We evaluate the aggregate productivity gains under a calibration in which intermediate inputs are complements, a calibration in which intermediate inputs are Cobb-Douglas (neither complements nor substitutes) and a calibration with our elasticity estimates.⁷⁷ The results are shown in the second to fourth columns of Table 8. The sectors of the economy in which a productivity increase would have the largest aggregate impact are ‘Agriculture’, ‘Textiles’ ‘Food & Beverages’, ‘Base Metals and Machinery’ and ‘Inland Transport’. The last column of Table 8 reports the ratio of the gains with our estimated elasticities compared to the other two benchmarks – we refer to this as the amplification effect of intermediate input substitution. On average, the gains with our elasticity estimates are 40% larger than in the ‘Cobb-Douglas’ calibration, and 56% larger than in the ‘Complements’ calibration. However there is a huge amount of dispersion in the amplification effect of intermediate input substitution for different sectors. Sectors with nearly no amplification include Agriculture (3%), Education (2%) and Health and Social Work (2%). Sectors with a large amplification include ‘Transport Equipment’ (69%), ‘Chemicals’ (76%), ‘Leather, Rubber & Plastics’ (78%) and ‘Other Non-Metallic Minerals’ (113%). This heterogeneity in amplification also changes the ranking of sectors in terms of the aggregate impact of a 50% productivity increase. For example, ‘Leather, Rubber and Plastics’ moves up from being the 14th most

that changes in consumer preferences (which are independent of price changes) are large. We will explore this further in future revisions of the paper.

⁷⁶Between 2005 and 2010, the sectors with 10-year TFP growth rates above 40% are all Services; Post & Telecommunications, Health & Social Work, Retail Trade, Air Transport and Financial Intermediation.

⁷⁷In the In the ‘Complements’ calibration, intermediate inputs are close to Leontief ($\theta = \theta^e = \theta^m = \theta^s = 0.1$). In the ‘Cobb-Douglas’ calibration all intermediate inputs have unitary elasticities of substitution ($\theta = \theta^e = \theta^m = \theta^s = 1$). In the ‘Substitutes’ calibration we use our estimated elasticities ($\theta = 1, \theta^e = \theta^m = \theta^s = 4.27$).

important sector to the 9th most important, and 'Chemicals' move up from 9th to 7th. In the next sub-section, we explain the mechanisms driving this amplification and explore possible sources driving the heterogeneity across sectors.

Table 8: Aggregate Productivity Gains from a 50% Increase in Sectoral Productivity

WIOD Sector	Complements ($\theta = \theta^z = 0.1$)	Cobb-Douglas ($\theta = \theta^z = 1$)	Substitutes ($\theta = 1, \theta^z = 4.27$)	Amplification, Substitutes vs. Complements/Cobb-Douglas
Agriculture, Hunting, Forestry and Fishing	19.62%	20.01%	20.57%	1.05 / 1.03
Textiles and Textile Products	7.52%	8.39%	12.93%	1.72 / 1.54
Food, Beverages and Tobacco	8.11%	8.31%	9.59%	1.18 / 1.15
Basic Metals and Machinery	6.01%	7.44%	11.43%	1.90 / 1.54
Inland Transport	6.54%	7.18%	10.16%	1.55 / 1.41
Retail Trade	4.71%	5%	5.95%	1.26 / 1.19
Transport Equipment	3.44%	4.03%	6.8%	1.98 / 1.69
Health and Social Work	3.72%	3.73%	3.79%	1.02 / 1.02
Chemicals and Chemical Products	3.04%	3.68%	6.49%	2.13 / 1.76
Financial Intermediation	3.02%	3.33%	4.79%	1.59 / 1.44
Real Estate Activities	3.02%	3.11%	3.51%	1.16 / 1.13
Other Community, Social and Personal Services	2.91%	3.1%	4.23%	1.45 / 1.36
Wholesale Trade	2.78%	3.03%	4.34%	1.56 / 1.43
Wood, Pulp and Paper Products	2.53%	2.92%	5.1%	2.01 / 1.75
Electricity, Gas and Water Supply	2.31%	2.83%	3.52%	1.52 / 1.24
Education	2.8%	2.81%	2.86%	1.02 / 1.02
Hotels and Restaurants	2.5%	2.55%	2.83%	1.13 / 1.11
Coke, Refined Petroleum and Nuclear Fuel	1.98%	2.30%	2.96%	1.49 / 1.29
Manufacturing, Nec; Recycling	1.71%	1.88%	2.63%	1.54 / 1.40
Leather, Rubber and Plastics	1.63%	1.87%	3.32%	2.04 / 1.78
Construction	1.25%	1.4%	2.26%	1.80 / 1.61
Renting of M&Eq and Other Business Activities	1.14%	1.20%	1.64%	1.45 / 1.37
Mining and Quarrying	0.98%	1.1%	1.35%	1.38 / 1.23
Post and Telecommunications	0.71%	0.74%	0.93%	1.32 / 1.25
Other Non-Metallic Mineral	0.59%	0.72%	1.52%	2.59 / 2.13
Other Transport Activities	0.48%	0.51%	0.72%	1.49 / 1.39
Sale, Maintenance and Repair of Motor Vehicles	0.38%	0.41%	0.6%	1.58 / 1.46
Air Transport	0.2%	0.21%	0.31%	1.57 / 1.46
Water Transport	0.16%	0.17%	0.26%	1.66 / 1.54
Average	3.3%	3.59%	4.74%	1.56 / 1.40

Notes: The 'Complements', 'Cobb-Douglas' and 'Substitutes' columns of the table report the % increase in aggregate consumption from a 50% increase in average plant TFP in the WIOD sector indicated by the corresponding row. The columns differ only in the elasticities of substitution between intermediate inputs that are used in the calibration and counterfactuals. In all columns θ^z is a stand-in for $\theta^c = \theta^m = \theta^s$. The 5th column report the ratio of gains reported in the 'Substitutes' column with those reported in the 'Complements' and 'Cobb-Douglas' columns. The last row of the table reports the across-sector average of the gains/amplification effects.

Mechanisms

Elasticities of substitution matter in this context because they introduce non-linearities in the relationship between sectoral productivity changes and aggregate productivity. A higher degree of substitutability leads to 'superstar' effects and larger aggregate gains from productivity improvements (Rosen (1981) and Jones (2011)). Locally (i.e. for small produc-

tivity shocks), however, the aggregate impact of a sectoral productivity shock is not very sensitive to the values of the elasticities of substitution. This follows from Hulten's Theorem (Hulten (1978)) which provides a set of conditions under which, in efficient economies, the first-order impact of a sectoral productivity shock is simply the sector's sales share of aggregate output.⁷⁸ The higher order terms, which become important for larger shocks, depend on how the size of the sector changes in response to the increase in productivity. When intermediate inputs are substitutable, firms will increase their expenditure on inputs coming from the sector whose productivity increased (and price fell). This will lead to an increase in the size of that sector, thereby amplifying the aggregate impact of the original productivity increase. Describing these non-linearities, and showing that short-run complementarities can amplify the losses from business cycle fluctuations in the U.S. is the main contribution of Baqaee and Farhi (2017). In contrast, we show that our micro-based estimates of high long-run elasticities of substitution have the opposite implication: the aggregate gains from sectoral productivity improvements in India could be significantly larger than previously thought.

In Figure 4, we show how the amplification effect of intermediate input substitution depends on the size of the sectoral productivity increases. For four 'Materials' sectors, we plot the model-implied % change in Indian aggregate consumption against the change in sectoral TFP.⁷⁹ The aggregate gains are nearly always largest in the 'Substitutes' case and lowest in the 'Complements' case.⁸⁰ The differences across calibrations are extremely small for small productivity changes, but are increasing as the changes become either more positive or more negative. In Table 22, Table 23 and Table 24 we report the amplification effects of intermediate input substitution for each sector of the Indian economy for 5%, 33% and 100% increases in sectoral productivity. In contrast to the 40% average amplification from a 50% productivity increase reported in Table 8, the average amplification from 5%, 33% and 100% increases are 8%, 26%, 72% respectively.

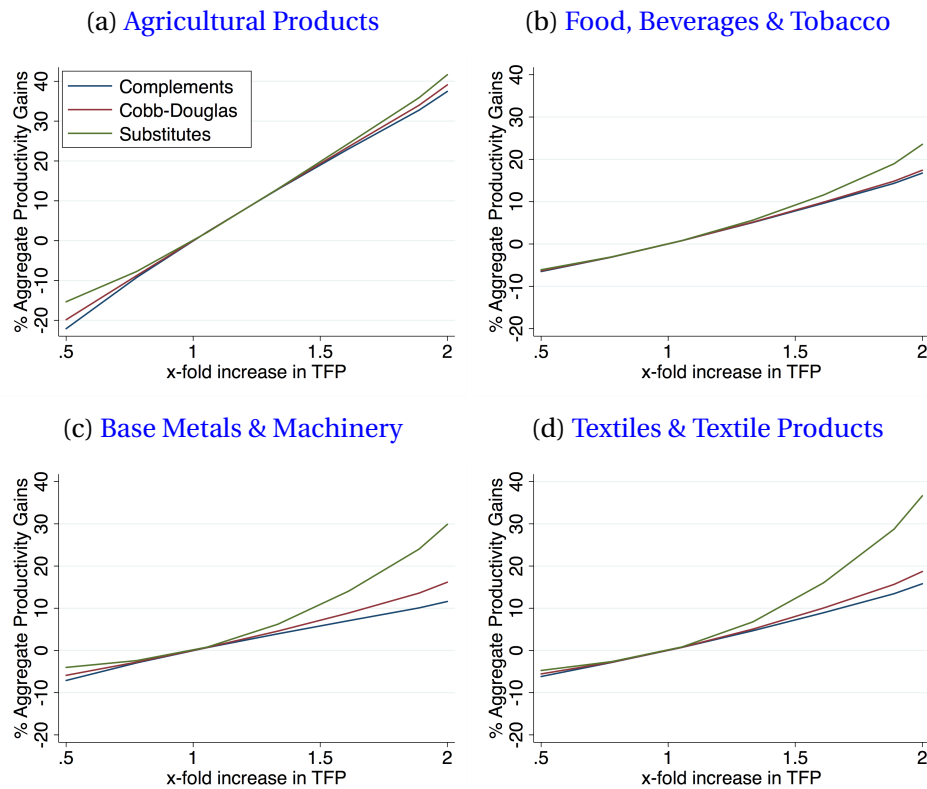
It is clear from Table 8 and Figure 4 that there is considerable heterogeneity across sectors in the amplification effect of intermediate input substitution. An important driver of this heterogeneity is the share of a sector's output that is used as an intermediate input. If a sector's output is used entirely in consumption, changes in that sector's productivity won't affect the relative price of intermediate inputs, and hence there will be no amplification through intermediate input substitution. We show in Figure 5 that the share of a sector's

⁷⁸Our model does not fit the conditions of Hulten's Theorem; the presence of distortions implies that the economy is not in an efficient equilibrium, and we allow for trade. However, we still find that, quantitatively, the key insight of Hulten's Theorem follows through.

⁷⁹Because labor is fixed, aggregate productivity changes are exactly equal to aggregate consumption changes.

⁸⁰Because the conditions of Hulten's Theorem do not hold in our model, it is not necessarily the case that the aggregate gains from a sectoral productivity increase are monotonically increasing in the elasticity of substitution.

Figure 4: Non-linear Impact of Increases in Sectoral TFP



We plot the % change in aggregate consumption implied by our model (calibrated to India in 1995) from an x-fold increase in the TFP of one sector. Each sub-figure corresponds to a different sector of the Indian economy. The x-axis correspond to the x-fold increase in the TFP of the corresponding sector: $x = 1$ implies no change in sectoral productivity, $x = 2$ implies a doubling of sectoral productivity.

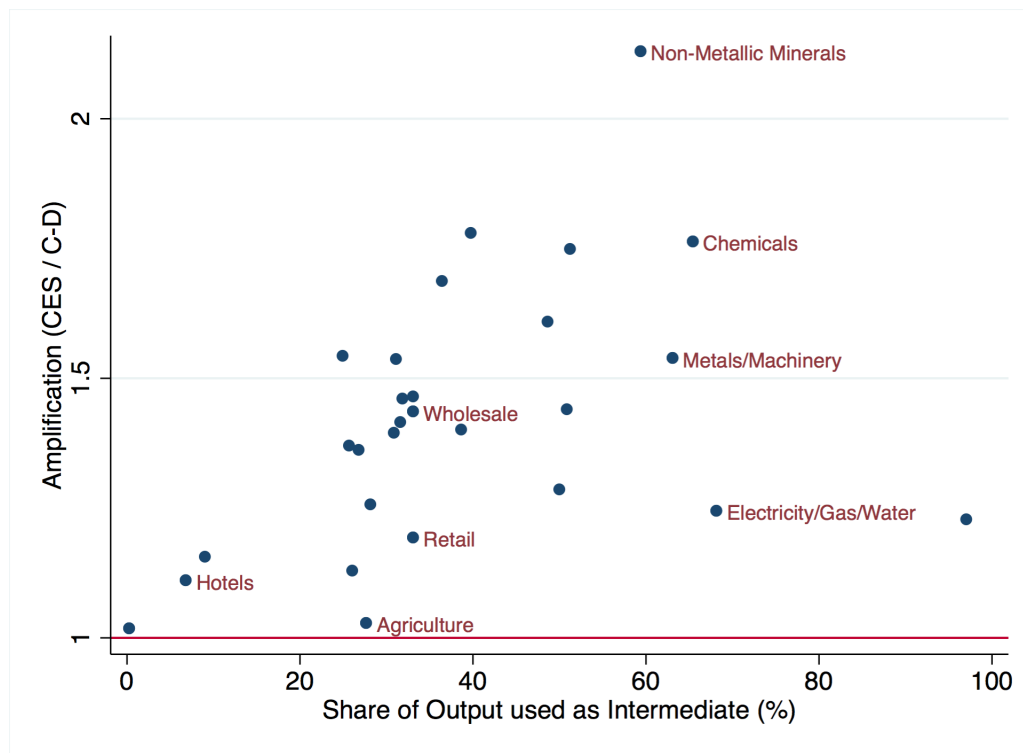
output used as an intermediate input is positively related to the amplification effect of intermediate input substitution. However, the amplification effects differ dramatically even for sectors with similar shares of output used as intermediates.⁸¹ We will further explore the sources of this heterogeneity in future versions of the paper.

It is worth noting the additional channel in our model through which sectoral spending shares respond to changes in relative intermediate input prices: reallocation across plants.⁸² Because firms differ in their expenditure shares on different intermediate inputs (within the same industry), they will experience different changes in marginal costs following a change in relative input prices. This induces a reallocation of inputs across plants – plants that intensively use the input whose relative price decreased will increase

⁸¹For example Chemicals, Metals & Machinery, Non-Metallic Minerals and Electricity, Gas & Water have amplification effects ranging from 24% to 112%.

⁸²This is not present in models with representative sectoral good producers such as Jones (2011), Atalay (2017) or Baqaee and Farhi (2017).

Figure 5: Amplification vs. Share of Sectoral Output Used As Intermediate



We plot the amplification effect from a 50% increase in sectoral TFP (see Table 8) against the share of sectoral output used as an intermediate input (as opposed to consumption).

their market share.⁸³ As shown in Oberfield and Raval (2014), the sector-level elasticity of substitution will be a weighted average of the production elasticities and demand elasticities (across plants), where the weights depend on the extent of heterogeneity in input shares.⁸⁴ The sector-level elasticity of substitution will therefore tend to be higher than the plant-level elasticity of substitution, provided that the elasticity of demand across plants is greater than the elasticity of substitution between inputs.⁸⁵ Reallocation across plants with different input shares can therefore somewhat offset the effect of complementarities in production. Another implication is that sector-level elasticities of substitution are not constant, and hence are not structural parameters.

⁸³E.g. a decrease in the price of cotton will lead to a reallocation of inputs towards more cotton-intensive firms.

⁸⁴They derive exact formulas for the sector-level and aggregate elasticity of substitution between labor and capital.

⁸⁵This is not the case in our baseline calibration, our estimate of the elasticity of substitution between materials is slightly higher than the elasticity of demand across plants.

An Alternative Mechanism: Multi-Product Plants

It is worth considering an alternative mechanism which could generate our empirical findings from Section 5. and how it relates to our quantitative model – plants switching between products. We can't empirically reject the possibility that plants respond to relative input price changes by changing the set of products they produce. This would be optimal when products vary in the intensity with which their production uses different intermediate inputs. With enough substitution between products, it would be possible to estimate a high elasticity of substitution between material inputs at the plant-level, even if the production function for each product is Leontief. In Appendix B1. we consider a simple alternative model and explore how sensitive our counterfactual results could be to this alternative mechanism. Interestingly, we find that even for large relative input price shocks, the change in sector-level relative spending shares is similar across the multi-product and single-product models (Figure 9). It is these changes in sector-level spending shares that drive the amplification effect of intermediate input substitution. These findings therefore suggest that our model could provide a reasonable approximation to alternative models with multi-product plants.

TFP Gaps

The size of sectoral TFP gaps between India and the U.S. provides a measure of how much productivity in Indian sectors could increase with the right technologies and policies. These TFP gaps can reflect differences in technology, product quality, allocative efficiency, etc... We measure these productivity gaps using the WIOD and SEA, combined with PPP prices from Inklaar and Timmer (2013). The way we construct these gaps is described in Appendix A8.. Sectoral TFP gaps between India and the U.S. are large and heterogeneous, as shown in the second column of Table 9, and the average sector is 55% as productive in India as it is in the U.S.⁸⁶ On average, the aggregate gains from closing TFP gaps are 80% larger with our estimated elasticities than in the 'Cobb-Douglas' calibration. These amplification effects are also highly heterogeneous, ranging from 376% for Non-Metallic Minerals to 17% for Agriculture, Hunting, Forestry and Fishing.

'Big Push' vs 'Superstars'

Our counterfactuals highlight how the aggregate gains from a productivity increase in a single sector of the economy depend on the elasticity of substitution between intermedi-

⁸⁶According to these measures, the least productive sector in India relative to the U.S. is Retail Trade, while the most productive is Chemicals and Chemical Products. However, given the likelihood of measurement error and the conceptual issues with measuring TFP (especially for Service sectors), we interpret the magnitude of these TFP gaps with caution. Note also that we exclude Education, Health & Social Work and Community & Social Services because TFP is unlikely to be an appropriate measure of productivity in these sectors. We also drop Air Transport and Real Estate Activities, because they have implausibly large and small measured TFP gaps respectively.

Table 9: Aggregate Productivity Gains from Closing Sectoral TFP Gaps

WIOD Sector	India / U.S. TFP	Complements ($\theta = \theta^2 = 0.1$)	Cobb-Douglas ($\theta = \theta^2 = 1$)	Substitutes ($\theta = 1, \theta^2 = 4.27$)	Amplification, Substitutes vs. Complements/Cobb-Douglas
Retail Trade	0.22	29.05%	33%	55.96%	1.93 / 1.7
Wholesale Trade	0.22	19.06%	21.29%	46.48%	2.44 / 2.18
Other Non-Metallic Mineral	0.32	2.43%	3.09%	14.69%	6.05 / 4.76
Mining and Quarrying	0.32	2.62%	3.58%	6.59%	2.51 / 1.84
Renting of M&Eq and Other Business Activities	0.34	4.35%	4.72%	9.33%	2.15 / 1.98
Agriculture, Hunting, Forestry and Fishing	0.35	63.31%	67.77%	74.37%	1.17 / 1.1
Wood, Pulp and Paper Products	0.37	8.23%	11.26%	38.9%	4.72 / 3.46
Coke, Refined Petroleum and Nuclear Fuel	0.39	4.43%	5.69%	8.42%	1.9 / 1.48
Basic Metals and Machinery	0.4	16.7%	25.33%	51.02%	3.06 / 2.01
Manufacturing, Nec; Recycling	0.41	4.85%	5.48%	10.84%	2.24 / 1.98
Sale, Maintenance and Repair of Motor Vehicles	0.42	1.01%	1.12%	2.55%	2.52 / 2.27
Textiles and Textile Products	0.42	21.88%	26.78%	58.44%	2.67 / 2.18
Hotels and Restaurants	0.42	7.2%	7.37%	8.73%	1.21 / 1.18
Water Transport	0.45	0.37%	0.41%	0.87%	2.33 / 2.12
Financial Intermediation	0.53	4.8%	5.5%	9.15%	1.91 / 1.66
Food, Beverages and Tobacco	0.6	10.75%	11.06%	13.21%	1.23 / 1.19
Transport Equipment	0.63	3.89%	4.58%	7.85%	2.02 / 1.71
Electricity, Gas and Water Supply	0.67	2.25%	2.72%	3.33%	1.48 / 1.23
Post and Telecommunications	0.7	0.59%	0.61%	0.72%	1.2 / 1.16
Other Transport Activities	0.71	0.39%	0.41%	0.53%	1.37 / 1.29
Leather, Rubber and Plastics	0.77	0.95%	1.05%	1.52%	1.61 / 1.45
Construction	0.91	0.26%	0.28%	0.35%	1.33 / 1.25
Inland Transport	1.2	-2.27%	-2.31%	-2.42%	1.07 / 1.05
Chemicals and Chemical Products	1.44	-2.11%	-2.01%	-1.8%	0.85 / 0.89
Average	0.55	8.54%	9.95%	17.48%	2.12/1.80

Notes: The 'Complements', 'Cobb-Douglas' and 'Substitutes' columns of the table report the % increase in aggregate consumption from closing the India/U.S. TFP gap in the sector indicated by the corresponding row. The columns differ only in the elasticities of substitution between intermediate inputs that are used in the calibration and counterfactuals. In all columns θ^2 is a stand-in for $\theta^e = \theta^m = \theta^s$. The 5th column report the ratio of gains reported in the 'Substitutes' column with those reported in the 'Complements' and 'Cobb-Douglas' columns. The last row of the table reports the across-sector average of the gains/amplification effects.

ate inputs. However, in order to evaluate the relative benefits of a homogeneous productivity increase in all sectors of the economy vs. in a single sector ('big push' vs. 'superstar' policies) we must also know how sensitive the gains from a homogeneous productivity increase in all sectors of the economy are to these elasticities. We calculate these gains and the associated amplification effect of intermediate input substitution with our quantitative model. We find that the amplification is considerably smaller than for productivity increases in a single sector. For example, the aggregate gains from a 5% productivity increase in all sectors of the economy are 10.01% with our 'Cobb-Douglas' calibration and 10.36% with our 'Substitutes' calibration. This is an amplification of only 3.5% compared to the average amplification of 40% reported in Table 8.⁸⁷ The amplification effects we find from single-sector productivity increases are therefore highly informative regarding the relative benefits of such 'big push' vs. 'superstar' policies. Finally, our analysis does not take a stand on what kinds of policies would be productivity enhancing, or what the costs of implementing such policies would be. In addition to financial costs, policy makers may have time constraints, political economy constraints, or distributional reasons for preferring certain policies to others. In the next sub-section we consider two specific types of policy reforms; reforms which reduce input misallocation, and India's trade liberalizations.

7.4. Counterfactuals: Policy Reforms

Misallocation / Allocative Efficiency

We evaluate the aggregate productivity gains from reducing dispersion in revenue distortions: i.e. improving allocative efficiency. We only consider the gains from removing 'revenue distortions' – we interpret all other heterogeneity in input shares across plants as due to technological differences.⁸⁸ Our counterfactual results are shown in Table 10. We find that the gains from removing all distortions are 16.24% in the 'Cobb-Douglas' calibration. The gains increase to 19.75% with our estimated elasticities; a 21.6% amplification. This amplification is smaller when we remove only within-sector dispersion in distortions; 6%. However the amplification is over 300% when we remove dispersion in across-sector distortions.⁸⁹ The difference stems from the fact that the main effect of removing within-sector dispersion in distortions is a small increase in sectoral TFP – following our discus-

⁸⁷We compare a 5% productivity increase in all sectors of the economy to a 50% productivity increase in a single sector of the economy because the average gains from a 50% increase in the productivity of a single sector are 4.74% – less than half as large as from a 5% productivity increase in all sectors. The amplification is 7.9% and 11.2% for a 33% and 50% productivity increase in all sectors of the economy respectively.

⁸⁸An alternative interpretation is that this dispersion is due to heterogeneous input prices and/or input-specific distortions. We plan to explore this interpretation in future versions of the paper.

⁸⁹In our model this dispersion comes from heterogeneity in markups across Indian sectors estimated by De Loecker et al. (2016).

sion in the previous section, this implies little amplification. On the other hand, the gains from reducing dispersion in across-sector distortions is more sensitive to the value of the production elasticities because the extent of the misallocation is worse when inputs are more substitutable.⁹⁰ Our results highlight the potential aggregate losses resulting from dispersion in markups across sectors.⁹¹

Table 10: Allocative Efficiency & Trade Liberalization Counterfactuals

Counterfactual Exercise	Complements ($\theta = \theta^z = 0.1$)	Cobb-Douglas ($\theta = \theta^z = 1$)	Substitutes ($\theta = 1, \theta^z = 4.27$)
<i>Allocative Efficiency</i>			
Across and Within Industry ($\tau_{ij} = 0$)	15.78%	16.65%	20.55%
Within Industry ($\tau_{ij} = \tau_j$)	11.82%	12.08%	12.82%
Across Industry ($\tau_j = 0$)	0.10%	0.24%	1.11%
<i>Trade Liberalization</i>			
$\Delta \ln P_k^I$	2.20%	2.35%	2.73%

Notes: The results in the table contrast the the % gains predicted by our model for various counterfactuals described in the leftmost column. $\theta_z = 1$ is used as a stand in for $\theta_e = \theta_m = \theta_s = 1$, and similarly for $\theta_z = 4.27$.

Trade Liberalization

Finally, we use our calibrated model to evaluate the expected gains from India's trade liberalization from the perspective of the Indian government in 1989. Because the WIOD only goes back as far as 1995, we first construct 'pseudo-1989' expenditure shares for the Indian economy by reverse engineering the trade liberalization using our 1995 calibration.⁹² Our counterfactual involves reducing sectoral import prices to match the observed reduction in import tariffs in that sector. Our main result is shown in Table 10. We find that the aggregate gains from the reduction in import prices increase from 2.20% when intermediate inputs are complements, to 2.35% when they are neither complements nor substitutes (Cobb-Duglas), to 2.73% with when they are substitutes. Our estimated gains

⁹⁰This is because quantities of inputs move more in response to sectoral distortions when inputs are more highly substitutable. This implies a larger reduction in allocative efficiency. On the flip side, if all sectors were perfectly complementary (Leontief), then there would no misallocation resulting from sectoral distortions.

⁹¹This is related to recent work by [Caliendo et al. \(2017\)](#) who focus on distortions in the world input-output matrix.

⁹²We increase import prices in each sector by the amount that import tariffs fell. We use our 'Substitutes' calibration when implementing this step.

are 24% larger relative to the ‘Complements’ benchmark, and 16% larger relative to the ‘Cobb-Douglas’ benchmark. It should be noted that our exercise does not take into account the pro-competitive effects of India’s trade liberalization (reduction in markups due to competition), nor the possibility that markups increased in response to the reduction in marginal costs (as found in [De Loecker et al. \(2016\)](#)). However, our exercise illustrates how the gains from trade can be amplified through intermediate input substitution.

8. Conclusion

To what extent should economic development policies target specific sectors of the economy or follow a ‘big push’ approach of advancing all sectors together? Our paper shows how the aggregate gains from productivity increases in individual sectors of the economy depend on how easily firms can substitute between intermediate inputs sourced from different sectors. Using rich micro-data and a natural policy experiment, we provide empirical evidence supporting a high long-run elasticity of substitution between material inputs used by Indian manufacturing plants. We find that the aggregate gains from a 50% productivity increase in any one sector of the Indian economy are on average 40% larger with our estimated elasticities. These results provide new insights into the importance of intermediate input substitution in amplifying policy reforms targeting specific sectors. Our paper also leaves many unanswered questions. Which intermediate inputs are easier/harder to substitute around? How important could a few low substitutability inputs be in holding back economic development? What are the costs associated with long-run adjustments to relative input price changes? These are important questions which we plan to pursue in future work.

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Appendix

A Data Appendix

A1. ASICC Classification

Table 11: Categories of Energy, Material and Service Inputs

Energy	Materials (1-digit ASICC)	Services
Coal (including Coke)	Animal & Vegetable Products, Beverages & Tobacco	Banking charges
Lignite	Ores & Minerals	Insurance charges
Coal Gas	Chemicals	Printing and Stationery
Liquefied Petroleum Gas	Rubber, Plastic & Leather	Postage, Telephone and Telex Expenses
Natural Gas	Wood, Cork, Thermocol and Paper	Inward and Outward Freight and Transportation Charges
Petrol and Aviation Petrol	Textile & Textile Articles	Printing and Stationery
Diesel Oil	Base Metals, Machinery Equipment & Parts	
Furnace Oil	Railways/Airways/Ships & Transport Equipment	
Firewood (Including Charcoal)	Other Manufactured Articles	
Biomass		
Purchased Electricity		
Purchased Water		
Lubricating Oil		

A2. 'ASI Item Code' and ASICC Concordance

Table 12: Examples from Concordance of 'ASI Item Code' classification to ASICC

NIC87-Item Code	Item Code Description	ASICC 5d (1)	ASICC 5d Description (1)	ASICC 5d (2)	ASICC 5d Description (2)	ASICC 3d	ASICC 3d Description
2010-1002	Dried Milk Powder	11406	Powder Milk	-	-	114	Dairy Products, Poultry, Birds, Egg, Honey & Other
3314-1006	Steel Ingots	71126	Ingot, Iron/Steel	-	-	711	Pig Iron/Ferro Alloy etc. in Primary Form
2001-1007	Mutton	11204	Mutton, Fresh/Frozen	11212	Mutton, Cooked (Not Canned)	112	Meat & Meat Products Edible
3806-1006	Brass Tubes / Rods	72232	Pipes & Tubes, Brass	72241	Sheets / Strips, Rods, Brass	722	Copper and Copper Alloy, Worked
2340-2032	Dyes	-	-	-	-	351	Dyeing, Tanning materials and their derivatives
3416-2007	Nickel Salt	-	-	-	-	723	Nickel and Nickel Alloys, Refined or Not, Unwrought

A3. WPI and ASICC Concordance

Table 13: Examples from Concordance of WPI classification to ASICC

WPI Product	ASICC5 (1)	ASICC5 Description (1)	ASICC5 (2)	ASICC5 Description (2)	ASICC5 (3)	ASICC5 Description (3)
Raw Wool	62101	Raw Wool	-	-	-	-
Rape & Mustard Oil	12515	Oil, Mustard	12518	Oil, Rapeseed	-	-
PVC Pipes & Tubings	42202	Pipe, Plastic/PVC (Non-Conduit)	42213	Tube, Plastic (Flexible/Non-Flexible)	-	-
Vat Dyes (Indigo Solubilised & Others)	35153	Dye, Vat Stuff (Indanthrene)	35154	Dye, Vat	-	-
T.V. Sets AC	78255	T.V. Set (B/W)	78256	T.V. Set (Colour)	78254	T.V. Kits

A4. Annual Survey of Industries

A4.1. Sampling

ASI sampled plants fall into two ‘schemes’: *Census* and *Sample*. *Census* plants, which include all plants with more than 100 workers (except in 1997 when the threshold was increased to 200 workers), are surveyed every year. Also included in the *Census* scheme are plants in 12 less industrially developed states, plants that file joint returns (plants under the same management in the same 4-digit industry and in the same state are allowed to file a single joint return), plants belonging to a state \times 4-digit industry group with fewer than 4 plants and plants belonging to a state \times 3-digit industry group with fewer than 20 plants.⁹³ The remaining plants fall into the *Sample* scheme and are sampled at random within state \times 3-digit industry category. One third of plants within each state \times 3-digit industry group are sampled. Sampling weights are provided in the survey.

A4.2. Panel Identifiers

We use an older version of the ASI surveys provided by the Indian Ministry of Statistics and Programme Implementation (MOSPI) which contain panel identifiers, enabling us to track plants over time. Merge files are available for download from Stephen D. O’Connell’s website: <http://www.stephenoconnell.org/codedata/>. We confirm the validity of the panel identifiers by checking the consistency of reported year of birth of the plant across survey years. The reporting of year of birth exactly matches for just over 70% of panel plants between 1989 and 1995-1997.

⁹³The less industrially developed states during our time period included Himachal Pradesh, Jammu & Kashmir, Manipur, Meghalaya, Nagaland, Tripura & Pondicherry, A & N Islands, Chandigarh, Goa, Daman & Diu and D & N Haveli.

Table 14: ASI Sample Statistics

	Full Sample	Panel Plants	Estimation Sample
<i>1989 ASI Survey</i>			
# Plants	34,987	13,322	8,080
Median Age	11	13	15
Median/Mean Labor	28/140	54 / 236	86 / 293
Median # Material Inputs Used	3	4	4
Share of Aggregate Output	100%	70.4%	51.4%
Share of Aggregate Labor	100%	57.7%	42.8%
<i>1996 ASI Survey</i>			
# Plants	43,039	10,925	7,177
Median Age	12	20	21
Median/Mean Labor	28/129	55 / 236	82 / 281
Median # Material Inputs Used	4	4	4
Share of Aggregate Output	100%	43.9%	32.9%
Share of Aggregate Labor	100%	40.7%	31.2%

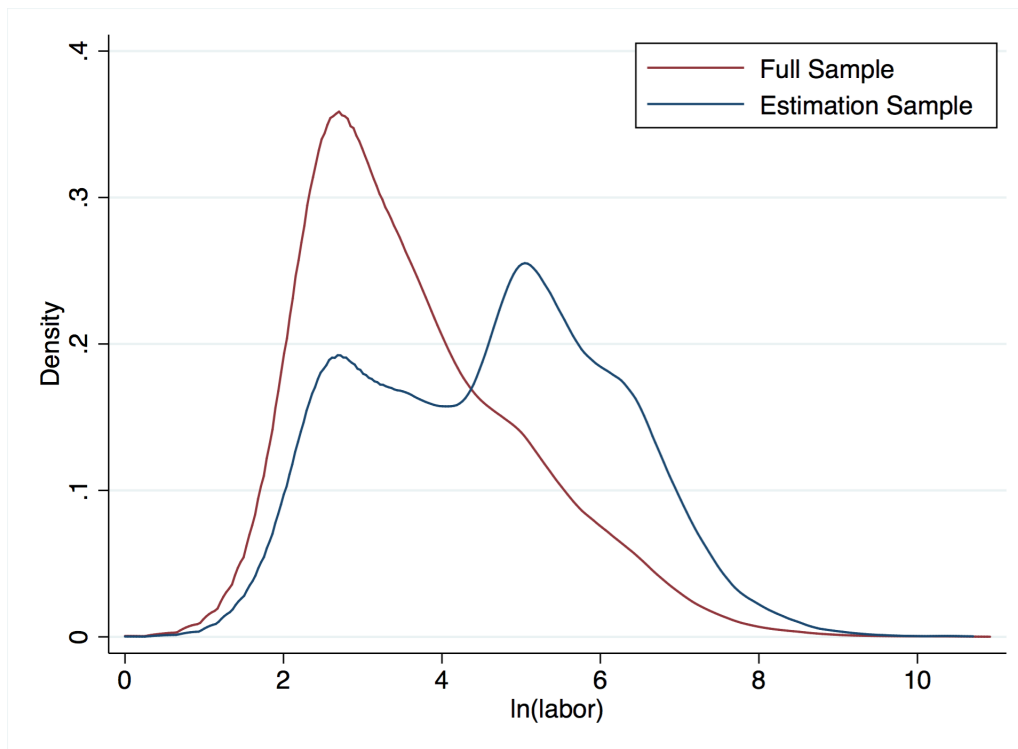
Notes: The statistics reported are constructed from the 1989-90 and 1996-97 ASI surveys. The 'Full Sample' column reports statistics for all 'open' manufacturing plants within NIC87 industries 2000-3999 with non-missing output, labor, intermediates and age. The 'Panel Plants' column restricts the sample to plants that appear in 1989 and at least one year between 1995 and 1997. The 'Estimation Sample' column restricts the sample to panel plants that appear in our sample estimating θ_m . Changes in the sample between the 'Panel Plants' and 'Estimation Sample' columns result from dropping plants that do not report at least two 1-digit ASICC material input categories (for which we have measures of prices and tariffs) in 1989 and at least once between 1995 and 1997. The changes in median age for panel plants between 1989 and 1996 may not exactly consistent due to misreporting. The 'Median # Inputs Used' row reports the median number of 1-digit ASICC material inputs reported by the plant.

A5. Trade Liberalization

We leave out 1993 from Figure 1 due to suspected mismeasurement in our tariff data for that year. The raw data indicates that from 1992 to 1993 tariffs rebounded from 56% to 77%. However we find no reference to any tariff increases in the budget reports from 1991 to 1994. We also compare predicted customs revenue based on HS-level import values and the raw tariff data to the official reports of customs revenue from the IMF Government Financial Statistics database. Using the raw tariff data, we find that predicted customs revenue overstates reported customs revenue by 130%. Replacing the raw 1993 tariffs with the average of the 1992 and 1994 tariffs we find that predicted customs revenue only overstates reported customs revenue by 20%. Unless otherwise specified, in all future specifications we replace the raw 1993 tariff with an average of the 1992 and 1994 tariffs on that input.

A6. ASI: Additional Figures & Tables

Figure 6: Labor Distribution in Full Sample and Estimation Sample



The figure shows the kernel density plots (with a bandwidth of .2) of $\ln(\text{labor})$ in the 'Full Sample' of ASI plants and in the 'Estimation Sample'. We pool the years 1989 and 1995-1997. Other summary statistics comparing the 'Full Sample' and 'Estimation Sample' are shown in Table 14.

Table 15: Aggregate Shares of 1-digit ASICC Material Inputs

Material Input Category	1989	1995	1996	1997
1. Animal & Vegetable Products, Beverages & Tobacco				
Full Sample	24.7%	18.8%	20.4%	24.7%
Estimation Sample	26.0%	18.7%	23.5%	28.2%
2. Ores & Minerals				
Full Sample	15.6%	10.5%	12%	13.1%
Estimation Sample	19.3%	15.6%	17.0%	23.8%
3. Chemicals				
Full Sample	10.1%	12.1%	13%	13.8%
Estimation Sample	10.4%	10.3%	10.3%	10.4%
4. Rubber, Plastic & Leather				
Full Sample	5.7%	6.1%	5.9%	5.0%
Estimation Sample	5.3%	4.8%	4.9%	4.0%
5. Wood, Cork, Thermocol, Paper				
Full Sample	4.0%	3.8%	3.9%	2.9%
Estimation Sample	4.5%	3.8%	4.1%	3.3%
6. Textiles & Textile Articles				
Full Sample	13.7%	12.1%	11.9%	14.6%
Estimation Sample	13.2%	10.5%	10.2%	12.0%
7. Base Metals, Machinery Equipment & Parts				
Full Sample	24.5%	34.1%	30%	23.9%
Estimation Sample	19.4%	34.4%	27.2%	16.8%
8. Railways/Airways/Ships & Transport Equipment				
Full Sample	0.4%	1.0%	1.3%	0.7%
Estimation Sample	0.6%	1.0%	1.6%	0.8%
9. Other Manufactured Articles				
Full Sample	1.4%	1.7%	1.6%	1.4%
Estimation Sample	1.2%	1.0%	1.0%	0.8%

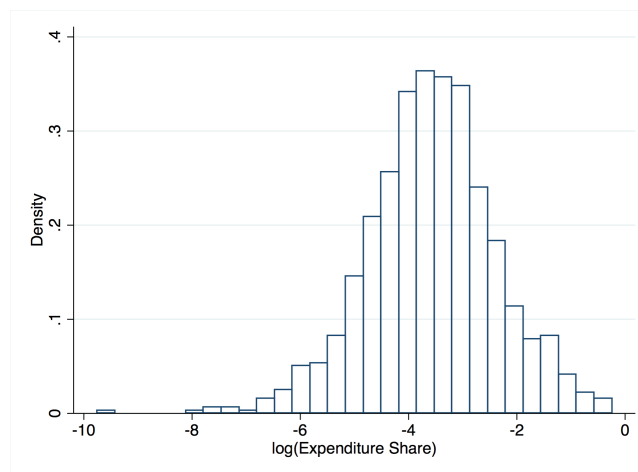
The statistics reported are constructed from the 1989 and 1995-1997 ASI surveys. The 'Full Sample' corresponds to all plants in the ASI that are 'open' manufacturing plants within NIC87 industries 2000-3999 with non-missing output, labor, intermediates and age. The 'Estimation Sample' column restricts the sample to panel plants that appear in our sample estimating θ_m .

Table 16: Extensive Margin of Input Use

	1-digit ASICC Material Inputs		3-digit ASICC Material Inputs	
	Share	Value Share	Share	Value Share
Inputs Dropped	11.6%	3.0%	41.0%	17.0%
Inputs Added	21.5%	8.1%	54.2%	26.6%

The reported statistics are constructed from the 1989 and 1995-1997 ASI surveys. The 'Inputs Dropped' row reports the average (value) share of inputs that were used by plants in 1989 but not between 1995 and 1997. The 'Inputs Added' row reports the average (value) share of inputs that were used by plants between 1995 and 1997 but not in 1989.

Figure 7: Histogram of Log(Spending Shares) on Material Input 'Textiles' in Industry 'Manufacture of Vegetable Oils and Fats Through 'Ghanis'



The figure is a histogram of log(spending shares) on the 1-digit ASICC category 'Textiles' in the industry 'Manufacture of Vegetable Oils and Fats Through 'Ghanis' (NIC87 = 2111). The dispersion in shares is calculated in 1996 for 464 plants

A7. Additional Empirical Results

Table 17: 1985-1988 Industry Pre-Trends

<i>Dependent Variable</i> (Tariff Changes)	1989-95	1989-96	1989-97
<i>Independent Variable</i>			
1985-88 Real Output Growth	-0.004 (0.005)	-0.004 (0.006)	-0.005 (0.005)
1985-88 Nominal Output Growth	-0.004 (0.005)	-0.004 (0.006)	-0.005 (0.005)
1985-88 Labor Growth	-0.001 (0.006)	-0.000 (0.007)	-0.003 (0.005)
1985-88 Capital Stock Growth	-0.004 (0.005)	-0.004 (0.00)	-0.006 (0.004)
1985-88 TFP Growth	0.011 (0.012)	0.017 (0.013)	0.005 (0.010)
1985-88 Output Price Change	-0.045 (0.052)	-0.017 (0.054)	0.0339 (0.044)

This table reports the coefficients from regressions of 1985-1988 4-digit industry growth rates of real output, nominal output, labor, capital, TFP and prices on the log-change in output tariffs between 1989 and 1995-1997. Output tariffs are the tariffs applied to the output from that industry. An observation is a 4-digit industry, and there are 298 observations in each regression. Standard errors are robust. All variables except for the change in tariffs and the change in output prices are winsorized at the 1% level to deal with outliers. All results are robust to using industry pre-trends between 1985 and 1989.

Table 18: Summary Statistics of Variables Used in Estimation

Variable	Mean	Standard Deviation
$\Delta \ln \left(\frac{\tilde{P}_{jik}^m \tilde{M}_{jik}}{\tilde{P}_{ji}^m \tilde{M}_{ji}} \right)$	-0.122	1.41
$\Delta \ln \left(\tilde{P}_{jk}^m \right)$	0.562	0.123
$\Delta \ln(1 + \tilde{\tau}_{jk})$	-0.25	0.164
$\Delta \ln \left(\frac{\tilde{P}_{ji}^m \tilde{M}_{ji}}{\tilde{P}_{ji}^z \tilde{Z}_{ji}} \right)$	-0.336	1.291
$\Delta \ln \left(\frac{\tilde{P}_{jk}^m}{\tilde{P}_{jk}^z} \right)$	-0.508	0.150
$\Delta \ln(1 + \tilde{\tau}_j)$	-0.267	0.140

In this table we report some summary statistics for the variables used in our estimation of θ_m . In the first row we report the mean and standard deviation of the log-change of expenditure shares. In the second row we report the mean and standard deviation of log-changes in prices. In the third row we report the mean and standard deviation of log-changes in lagged tariffs.

Table 19: Robustness of θ_m Estimates

Specification	First-Stage	Second Stage	# Obs	# Plants	Plant FEs	Input FEs
<i>Trimming/Winsorizing Δ Expenditure Shares</i>						
1% trimming	0.254*** (0.052)	-3.265*** (0.920)	21,673		YES	NO
2% trimming	0.254*** (0.053)	-2.900*** (0.837)	20,985		YES	NO
5% trimming	0.250*** (0.057)	-2.412*** (0.767)	18,962		YES	NO
1% winsorizing	0.253*** (0.051)	-3.678*** (1.068)	22,000		YES	NO
2% winsorizing	0.253*** (0.051)	-3.556*** (1.028)	22,000		YES	NO
5% winsorizing	0.253*** (0.051)	-3.174*** (0.914)	22,000		YES	NO
<i>Winsorizing Δ Prices, Tariffs, Expenditures</i>						
1% winsorizing	0.253*** (0.050)	-3.814*** (1.097)	22,000		YES	NO
<i>Excluding Primary Inputs</i>						
Non-Primary-Food Inputs Only	0.261*** (0.046)	-4.596*** (1.410)	16,157		YES	NO
Manufactured Inputs Only	0.366*** (0.034)	-4.261*** (1.074)	11,091		YES	NO
<i>Cutoffs: Value Shares # Inputs</i>						
0.1% Value Share, Top 5 Inputs	0.257*** (0.054)	-3.557*** (1.073)	21,040		YES	NO
1% Value Share, Top 2 Inputs	0.278*** (0.093)	-3.811*** (0.915)	12,452		YES	NO
<i>Twoway Clustering Standard Errors</i>						
4-digit industry, 2-digit industry \times input	0.253*** (0.058)	-3.720*** (1.168)	22,000		YES	NO
<i>Share of Materials Concurred in 1989</i>						
90% minimum concurred	0.252*** (0.060)	-3.603*** (1.229)	16,931		YES	NO
99% minimum concurred	0.254*** (0.071)	-3.282*** (1.334)	13,203		YES	NO
<i>Input Fixed Effects</i>						
Baseline	0.166** (0.082)	-3.693 (2.270)	22,000		YES	YES
0.1% Value Share Cutoff, Top 5 Inputs	0.175*** (0.082)	-3.548* (2.087)	21,040		YES	YES
1% Value Share Cutoff, Top 2 Inputs	0.239** (0.095)	-3.316** (1.646)	13,203		YES	YES

Table 20: Sensitivity of θ_m Estimates to Dropping Individual Inputs

Input Dropped	First-Stage	Second Stage	# Obs	# Plants
1. Animal & Vegetable Products, Beverages & Tobacco	0.241*** (0.040)	-4.036*** (1.214)	18,667	
2. Ores & Minerals	0.319*** (0.052)	-2.943*** (0.661)	19,737	
3. Chemicals	0.260*** (0.060)	-4.050*** (1.232)	16,927	
4. Rubber, Plastic & Leather	0.237*** (0.056)	-4.140*** (1.316)	19,218	
5. Wood, Cork, Thermocol, Paper	0.251*** (0.051)	-3.513* (1.811)	17,972	
6. Textiles & Textile Articles	0.171*** (0.053)	-6.894*** (2.318)	17,617	
7. Base Metals, Machinery Equipment & Parts	0.268*** (0.096)	-1.546*** (0.582)	15,541	
8. Railways/Airways/Ships & Transport Equipment	0.253*** (0.051)	-3.724*** (1.077)	21,998	
9. Other Manufactured Articles	0.253*** (0.051)	-3.730*** (1.091)	21,465	

A8. World Input-Output Database

Table 21: World Input-Output Database Industries

Materials	Energy	Services
Agriculture, Hunting, Fishing & Forestry	Electricity, Gas and Water Supply	Sale, Maintenance and Repair of Motor Vehicles and Motorcycles; Retail Sale of Fuel
Mining and Quarrying	Coke, Refined Petroleum and Nuclear Fuels	Wholesale Trade and Commission Trade, Except of Motor Vehicles and Motorcycles
Food, Beverages and Tobacco		Retail Trade, Except of Motor Vehicles and Motorcycles; Repair of Household Goods
Other Non-Metallic Minerals		Inland Transport
Chemicals and Chemical Products		Water Transport
Leather, Rubber and Plastics		Air Transport
Wood, Pulp and Paper Products		Other Supporting and Auxiliary Transport Activities; Activities of Travel Agencies
Textiles and Textile Products		Post and Telecommunications
Basic Metals and Machinery		Real Estate Activities
Transport Equipment		Renting of M&Eq and Other Business Activities
Manufacturing, Nec; Recycling		Construction
		Hotels and Restaurants
		Financial Intermediation
		Education
		Health & Social Work
		Other Community, Social and Personal Services

A9. Additional Results from Quantitative Model

Table 22: Aggregate Productivity Gains from a 5% Increase in Sectoral Productivity

WIOD Sector	Complements ($\theta = \theta^z = 0.1$)	Cobb-Douglas ($\theta = \theta^z = 1$)	Substitutes ($\theta = 1, \theta^z = 4.27$)	Amplification, Substitutes vs. Complements/Cobb-Douglas
Agriculture, Hunting, Forestry and Fishing	0.74%	0.72%	0.69%	0.94 / 0.96
Food, Beverages and Tobacco	0.27%	0.27%	0.28%	1.04 / 1.03
Textiles and Textile Products	0.25%	0.26%	0.28%	1.15 / 1.11
Inland Transport	0.24%	0.25%	0.3%	1.24 / 1.18
Basic Metals and Machinery	0.23%	0.24%	0.27%	1.17 / 1.11
Retail Trade	0.19%	0.18%	0.17%	0.93 / 0.94
Financial Intermediation	0.13%	0.13%	0.13%	1.04 / 1.03
Chemicals and Chemical Products	0.12%	0.13%	0.15%	1.31 / 1.22
Health and Social Work	0.12%	0.12%	0.12%	1.01 / 1.01
Transport Equipment	0.11%	0.12%	0.14%	1.26 / 1.18
Real Estate Activities	0.12%	0.11%	0.1%	0.87 / 0.9
Electricity, Gas and Water Supply	0.11%	0.11%	0.12%	1.1 / 1.04
Other Community, Social and Personal Services	0.11%	0.11%	0.12%	1.15 / 1.12
Wholesale Trade	0.1%	0.11%	0.12%	1.17 / 1.13
Wood, Pulp and Paper Products	0.1%	0.1%	0.1%	1.04 / 1.02
Coke, Refined Petroleum and Nuclear Fuel	0.09%	0.09%	0.1%	1.21 / 1.13
Education	0.09%	0.09%	0.09%	1.02 / 1.01
Hotels and Restaurants	0.08%	0.08%	0.09%	1.05 / 1.04
Manufacturing, Nec; Recycling	0.06%	0.07%	0.08%	1.2 / 1.14
Leather, Rubber and Plastics	0.06%	0.06%	0.07%	1.26 / 1.18
Construction	0.05%	0.05%	0.06%	1.28 / 1.21
Mining and Quarrying	0.04%	0.04%	0.04%	1.04 / 1.02
Renting of M&Eq and Other Business Activities	0.04%	0.04%	0.05%	1.09 / 1.08
Post and Telecommunications	0.03%	0.03%	0.02%	0.87 / 0.9
Other Non-Metallic Mineral	0.02%	0.03%	0.04%	1.67 / 1.46
Other Transport Activities	0.02%	0.02%	0.02%	1.07 / 1.05
Sale, Maintenance and Repair of Motor Vehicles	0.01%	0.01%	0.02%	1.06 / 1.04
Air Transport	0.01%	0.01%	0.01%	1.1 / 1.07
Water Transport	0.01%	0.01%	0.01%	1.2 / 1.15
Average	0.37%	0.37%	0.4%	1.12 / 1.08

Notes: The 'Complements', 'Cobb-Douglas' and 'Substitutes' columns of the table report the % increase in aggregate consumption from a 5% increase in average plant TFP in the WIOD sector indicated by the corresponding row. The columns differ only in the elasticities of substitution between intermediate inputs that are used in the calibration and counterfactuals. In all columns θ^z is a stand-in for $\theta^c = \theta^{m} = \theta^s$. The 5th column report the ratio of gains reported in the 'Substitutes' column with those reported in the 'Complements' and 'Cobb-Douglas' columns. The last row of the table reports the across-sector average of the gains/amplification effects.

Table 23: Aggregate Productivity Gains from a 33% Increase in Sectoral Productivity

WIOD Sector	Complements ($\theta = \theta^z = 0.1$)	Cobb-Douglas ($\theta = \theta^z = 1$)	Substitutes ($\theta = 1, \theta^z = 4.27$)	Amplification, Substitutes vs. Complements/Cobb-Douglas
Agriculture, Hunting, Forestry and Fishing	12.89%	12.96%	13%	1.01 / 1
Food, Beverages and Tobacco	5.09%	5.18%	5.64%	1.11 / 1.09
Textiles and Textile Products	4.68%	5.07%	6.77%	1.45 / 1.34
Inland Transport	4.25%	4.6%	6.07%	1.43 / 1.32
Basic Metals and Machinery	3.95%	4.59%	6.23%	1.58 / 1.36
Retail Trade	3.13%	3.25%	3.54%	1.13 / 1.09
Transport Equipment	2.11%	2.37%	3.37%	1.6 / 1.42
Health and Social Work	2.31%	2.32%	2.35%	1.02 / 1.01
Chemicals and Chemical Products	2%	2.32%	3.51%	1.75 / 1.52
Financial Intermediation	2.05%	2.2%	2.8%	1.36 / 1.27
Real Estate Activities	2.01%	2.02%	2.1%	1.05 / 1.04
Other Community, Social and Personal Services	1.89%	1.99%	2.51%	1.33 / 1.26
Wholesale Trade	1.81%	1.95%	2.54%	1.4 / 1.31
Electricity, Gas and Water Supply	1.65%	1.91%	2.23%	1.36 / 1.17
Wood, Pulp and Paper Products	1.67%	1.83%	2.54%	1.53 / 1.39
Education	1.74%	1.74%	1.77%	1.02 / 1.01
Hotels and Restaurants	1.57%	1.6%	1.72%	1.1 / 1.08
Coke, Refined Petroleum and Nuclear Fuel	1.38%	1.56%	1.91%	1.38 / 1.22
Manufacturing, Nec; Recycling	1.12%	1.21%	1.55%	1.39 / 1.28
Leather, Rubber and Plastics	1.05%	1.17%	1.74%	1.66 / 1.49
Construction	0.84%	0.92%	1.33%	1.59 / 1.44
Renting of M&Eq and Other Business Activities	0.74%	0.77%	0.96%	1.3 / 1.24
Mining and Quarrying	0.68%	0.74%	0.84%	1.23 / 1.14
Post and Telecommunications	0.47%	0.48%	0.53%	1.12 / 1.1
Other Non-Metallic Mineral	0.39%	0.46%	0.84%	2.17 / 1.82
Other Transport Activities	0.31%	0.33%	0.41%	1.3 / 1.24
Sale, Maintenance and Repair of Motor Vehicles	0.25%	0.26%	0.33%	1.34 / 1.27
Air Transport	0.13%	0.14%	0.17%	1.36 / 1.28
Water Transport	0.1%	0.11%	0.15%	1.46 / 1.36
Average	2.15%	2.28%	2.74%	1.36 / 1.26

Notes: The 'Complements', 'Cobb-Douglas' and 'Substitutes' columns of the table report the % increase in aggregate consumption from a 33% increase in average plant TFP in the WIOD sector indicated by the corresponding row. The columns differ only in the elasticities of substitution between intermediate inputs that are used in the calibration and counterfactuals. In all columns θ^z is a stand-in for $\theta^c = \theta^m = \theta^s$. The 5th column report the ratio of gains reported in the 'Substitutes' column with those reported in the 'Complements' and 'Cobb-Douglas' columns. The last row of the table reports the across-sector average of the gains/amplification effects.

Table 24: Aggregate Productivity Gains from a 100% Increase in Sectoral Productivity

WIOD Sector	Complements ($\theta = \theta^z = 0.1$)	Cobb-Douglas ($\theta = \theta^z = 1$)	Substitutes ($\theta = 1, \theta^z = 4.27$)	Amplification, Substitutes vs. Complements/Cobb-Douglas
Agriculture, Hunting, Forestry and Fishing	37.45%	39.11%	41.65%	1.11 / 1.06
Textiles and Textile Products	15.81%	18.71%	36.65%	2.32 / 1.96
Food, Beverages and Tobacco	16.76%	17.44%	23.55%	1.41 / 1.35
Basic Metals and Machinery	11.61%	16.18%	29.88%	2.57 / 1.85
Inland Transport	12.83%	14.36%	22.87%	1.78 / 1.59
Transport Equipment	7.66%	10.16%	24.66%	3.22 / 2.43
Retail Trade	8.93%	9.77%	13.39%	1.5 / 1.37
Health and Social Work	7.83%	7.87%	8.04%	1.03 / 1.02
Chemicals and Chemical Products	5.87%	7.77%	17.58%	2.99 / 2.26
Financial Intermediation	5.47%	6.35%	11.13%	2.03 / 1.75
Other Community, Social and Personal Services	5.75%	6.23%	9.65%	1.68 / 1.55
Wood, Pulp and Paper Products	4.92%	6.18%	16%	3.25 / 2.59
Real Estate Activities	5.74%	6.1%	7.87%	1.37 / 1.29
Wholesale Trade	5.46%	6.05%	10.14%	1.86 / 1.68
Education	5.93%	5.96%	6.12%	1.03 / 1.03
Hotels and Restaurants	5.23%	5.34%	6.19%	1.19 / 1.16
Electricity, Gas and Water Supply	3.8%	5.11%	6.99%	1.84 / 1.37
Coke, Refined Petroleum and Nuclear Fuel	3.37%	4.14%	5.79%	1.72 / 1.4
Leather, Rubber and Plastics	3.27%	3.94%	9.98%	3.05 / 2.54
Manufacturing, Nec; Recycling	3.37%	3.78%	6.37%	1.89 / 1.69
Construction	2.37%	2.73%	5.3%	2.24 / 1.94
Renting of M&Eq and Other Business Activities	2.26%	2.43%	3.95%	1.75 / 1.63
Mining and Quarrying	1.66%	2%	2.85%	1.72 / 1.42
Post and Telecommunications	1.34%	1.46%	2.34%	1.74 / 1.6
Other Non-Metallic Mineral	1.13%	1.41%	4.11%	3.63 / 2.91
Other Transport Activities	0.95%	1.04%	1.84%	1.93 / 1.77
Sale, Maintenance and Repair of Motor Vehicles	0.74%	0.81%	1.57%	2.13 / 1.93
Air Transport	0.39%	0.43%	0.82%	2.08 / 1.9
Water Transport	0.32%	0.35%	0.68%	2.16 / 1.97
Average	6.49%	7.35%	11.65%	2.01 / 1.72

Notes: The 'Complements', 'Cobb-Douglas' and 'Substitutes' columns of the table report the % increase in aggregate consumption from a 100% increase in average plant TFP in the WIOD sector indicated by the corresponding row. The columns differ only in the elasticities of substitution between intermediate inputs that are used in the calibration and counterfactuals. In all columns θ^z is a stand-in for $\theta^c = \theta^m = \theta^s$. The 5th column report the ratio of gains reported in the 'Substitutes' column with those reported in the 'Complements' and 'Cobb-Douglas' columns. The last row of the table reports the across-sector average of the gains/amplification effects.

B Model Appendix

B1. Multiple Varieties per Plant

An alternative interpretation of our empirical findings is that ‘true’ plant production functions are Cobb-Douglas or Leontief but plants substitute between the different products they produce when input prices change.⁹⁴ How sensitive are our counterfactual results to this alternative interpretation? Precisely answering this question requires fully specifying and calibrating our general equilibrium model under the alternative set of assumptions. However, we can get an idea of the sensitivity of our results by considering a simplified model of one industry. The main question is how changes in relative input prices affect 1) the industry price index and 2) industry spending shares. If different models, when calibrated to the same data, make similar predictions for these two statistics, then the aggregate gains from a counterfactual productivity increase in one sector of the economy will be similar across models.⁹⁵

Consider the following industry model. There are N plants in the industry, each producing J varieties. The representative consumer has nested CES preferences over plants and varieties given by:

$$Q = \left(\sum_{i=1}^N Q_i^{\frac{\mu-1}{\mu}} \right)^{\frac{\mu}{\mu-1}}$$

$$Q_i = \left(\sum_{j=1}^J Q_{ij}^{\frac{\eta-1}{\eta}} \right)^{\frac{\eta}{\eta-1}}$$

This generates the following demand curve for plant output $P_i = PQ^{\frac{1}{\mu}} Q_i^{-\frac{1}{\mu}}$, and for each variety $P_{ij} = P_i Q_i^{\frac{1}{\eta}} Q_{ij}^{-\frac{1}{\eta}}$.⁹⁶ The industry price index is given by $P = \left(\sum_{i=1}^N P_i^{1-\mu} \right)^{\frac{1}{1-\mu}}$.⁹⁷ Plants produce each variety Q_{ij} using two inputs A and B and the following production function:

$$Q_{ij} = Z_{ij} \left((a_{ij}A)^{\frac{\xi-1}{\xi}} + (b_{ij}B)^{\frac{\xi-1}{\xi}} \right)^{\frac{\xi}{\xi-1}}$$

$\xi = 0$ is equivalent to a Leontief production function (no substitutability between inputs), while $\xi = 1$ is equivalent to a Cobb-Douglas production function. Plants take input prices P^A and P^B as given and are profit maximizing. We make the simplifying assumption that

⁹⁴This interpretation would only work if different products require different input spending shares.

⁹⁵The change in the industry price index captures the direct impact of the change in relative input prices on marginal costs. The change in industry spending shares captures the extent to which the original productivity shock will be amplified through changes in the input-output structure.

⁹⁶The nested CES demand system is a tractable and commonly used approach to modeling consumer preferences across firms and across products within firms. See for example [Hottman et al. \(2016\)](#).

⁹⁷Similarly, the plant price index is given by $P_i = \left(\sum_{j=1}^J P_{ij}^{1-\eta} \right)^{\frac{1}{1-\eta}}$

plants take the industry price index as given when choosing the total amount of output to produce, and take the plant price index as given when choosing how much to produce of each variety.

For given values of the elasticities, observed data on plant market shares, sales shares for each variety and input spending shares for each variety, we can back out all the parameters of the model. We can then conduct counterfactuals; in particular we can evaluate how the industry price index P and the industry spending share on input A changes in response to a change in P^A/P^B .

We simulate data for $N = 500$ plants, each producing $J = 10$ varieties. Plant market shares are lognormally distributed, the sales share of each variety is 10%, and spending shares on input A are independently uniformly distributed between 0 and 1 for each variety and plant. We set the elasticity of substitution $\mu = 3.94$, as in our baseline calibration. We then calibrate our model from the perspective of three researchers who make different structural assumptions regarding how plant output is produced:

- Researcher 1 only observes total plant sales and total plant spending on A and B, and so assumes that $J = 1$.
- Researcher 2 observes plant sales and spending for each variety, and assumes that $\xi = 1$; Cobb-Douglas production.
- Researcher 3 observes plant sales and spending for each variety, and assumes that $\xi = 0$; Leontief production.

All three researchers observe that the average relative spending share on input A across plants increases by 20% in response to a decrease in the relative price of input A by 6.25%.⁹⁸ Researcher 1 infers that $\xi = 4.3$, Researcher 2 infers that $\eta = 11.7$ and Researcher 3 infers that $\eta = 14.0$. They then each evaluate the counterfactual change in the industry price index and the change in the industry spending share on input A in response to larger relative price changes. These counterfactual changes are shown in Figures 8 and 9.

By construction, the changes in the industry price index and in the industry spending share on input A overlap across models for small changes in relative input prices. However, it can also be seen that all three models yield qualitatively and quantitatively similar predictions even for large changes in relative price changes (up to a 50% reduction). The change in the industry spending share is largest in the 1-variety model with CES production. This is because of the constant elasticity assumption. In the multiple-variety models there is greater concavity in the industry spending share changes as plants gradually exhaust their ability to substitute across varieties.⁹⁹ Productivity increases in individual sectors will therefore still be amplified through changes in the input-output structure, however this amplification may be somewhat dampened compared to our baseline estimates.

⁹⁸This 6.25% reduction in the relative price of input A is equivalent to the average price reduction induced by our tariff changes: 25% average reduction in tariffs with a pass-through rate of 25%.

⁹⁹The rate at which this concavity sets in is increasing in the elasticity of substitution across varieties η . In addition, with Leontief production the relationship between changes in the industry spending share and changes in relative input prices is non-monotonic.

Figure 8: Change in Industry Price Index

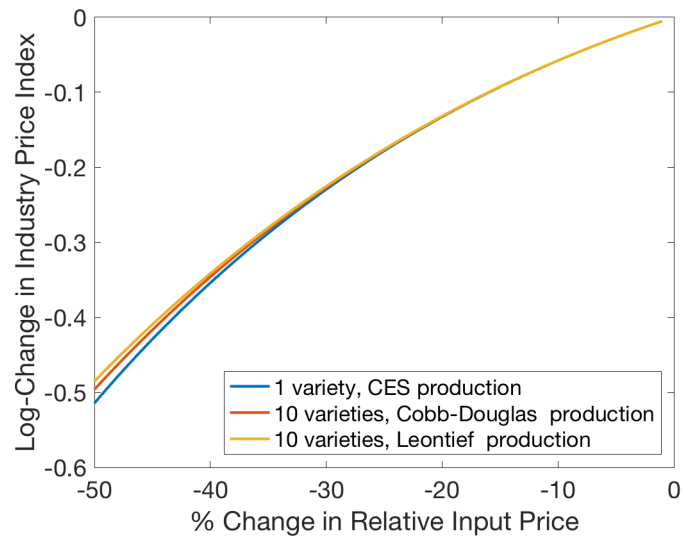


Figure 9: Change in Industry Spending Share

