The Aggregate Importance of Intermediate Input Substitutability

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Abstract

We estimate long-run elasticities of substitution between intermediate inputs for Indian manufacturing plants. India's trade liberalization in the early 1990s provides an ideal natural policy experiment, with permanent and heterogeneous tariff reductions inducing changes in relative prices which we use for identification. We find a high degree of substitutability at the plant-level between 8 broad categories of material inputs, significantly above the Cobb-Douglas benchmark of 1. In contrast, we find elasticities less than 1 between energy, materials, and services as well as between value added and intermediates. We embed our elasticities in a general equilibrium model with a rich input-output structure to quantify their importance. Relative to a Cobb-Douglas benchmark, the aggregate gains from trade are 9% larger when intermediate inputs are substitutes, and come hand in hand with 40% more reallocation of labor across sectors. Furthermore, the aggregate gains from closing the India-U.S. TFP gap in any one sector are on average 29% larger with our estimated elasticities; losses from misallocation of intermediate inputs are more than 3 times larger.

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1. Introduction

Modern production often involves multiple firms operating in complex supply chains. A key characteristic of the production process is the degree of substitutability of inputs. This governs how the economy responds — in both direction and magnitude — to shocks such as technological change or policies such as import tariffs. However, as input adjustments take time and may be costly, the degree of substitutability can depend on the time horizon as well as the permanence of the shock. The degree of substitutability of inputs over the long run is therefore a crucial ingredient for understanding economic development and the long-run impacts of macroeconomic and trade policies. Despite its importance, there is scant empirical evidence on firms' ability to substitute in response to shocks over longer time horizons.

In this paper, we estimate long-run elasticities of substitution for intermediate inputs of Indian manufacturing plants. Using India's trade liberalization as a natural experiment, we estimate an elasticity of substitution of around 3 between eight broad categories of material inputs. In contrast, we find evidence of complementarities between energy, materials, and services as well as between intermediates and value-added. We incorporate our elasticity estimates into a general equilibrium model with input-output linkages and calibrate it to the Indian economy. Our estimated deviations from the Cobb-Douglas benchmark of 1 amplify the gains from India's trade liberalization by nearly 10% and can even reverse the direction of labor reallocation across sectors. Moreover, these deviations imply 29% larger gains on average from closing India-U.S. sectoral TFP gaps and losses from misallocation due to intermediate input distortions that are more than three times larger.

Our estimate of the *long-run* elasticity of substitution between intermediate inputs of around 3 differs substantially from existing short-run estimates. Boehm, Flaaen and Pandalai-Nayar (2019), Barrot and Sauvagnat (2016), and Atalay (2017) find elasticities close to 0 over horizons of one year or less. Our paper adds to this literature by highlighting that the time horizon as well as the nature of price changes are crucial. In our setting, plants faced a *permanent* rather than *transitory* change in relative prices and had up to 7 years to adapt their input mix. In addition, we complement the quantitative macroeconomics and trade literature by studying how substitutability of intermediate inputs over the long run amplifies the gains from trade, sectoral TFP increases, and losses from misallocation.

Using rich data on intermediate input use by manufacturing plants from the 1989 and 1996 Indian Annual Survey of Industries (ASI), we estimate how plants' intermediate spending shares changed in response to changes in intermediate input prices. These moments identify the long-run elasticities of substitution between intermediate inputs in a standard constant elasticity of substitution (CES) production function. We choose a nesting structure consistent with KLEMS national accounting. The upper nest of this CES production function comprises a capital-labor bundle and intermediate inputs. The upper nest of intermediate inputs consists of energy, materials and services. The lower nest of material inputs contains 8 broad categories of materials. These include categories such as Metals, Rubber and Plastics, and Wood and Paper Products. The estimating equations are linear regressions of changes in relative input expenditures on changes in relative input prices.

To overcome the well-known problem of separately identifying elasticities from factor-biased technologies (Diamond and McFadden (1978); Antràs (2004)), we use India's 1991 trade liberalization as a natural policy experiment. More precisely, we instrument for changes in domestic input prices using changes in import tariffs. India's trade liberalization is an ideal setting because it was large, unexpected, and without much scope for lobbying or political interference (Topalova, 2010). Moreover, import tariffs changed heterogeneously across highly disaggregated inputs in an arguably quasi-random way; initial tariffs varied widely but converged to around 30% by the end of the liberalization. These heterogeneous changes induced large changes in relative input prices. The granularity of the price and tariff changes allows us to control for aggregate trends in expenditure shares and prices across each of the 8 broad categories of material inputs. Our identifying variation then exploits the fact that plants used 450 sub-categories of inputs with varying intensities and therefore saw different changes in their relative prices for each of the 8 broad categories of materials.

Our estimate of the plant-level elasticity of substitution between material input categories is 3.1. The 95% confidence interval – [1.8, 4.4] – lies significantly above the Cobb-Douglas benchmark. Between energy, materials, and services, we estimate a plant-level elasticity of substitution of 0.4, indicating that inputs are complements at higher levels of aggregation even in the longer run. Similarly, we estimate the elasticity between the capital-labor bundle and intermediates to be 0.6. Our identification strategy using the trade liberalization is important to recover the correct elasticity. The OLS estimate of the elasticity of substitution between material inputs, while still significantly larger than one, is lower than the IV estimate, as would be expected due to both simultaneity bias and measurement error.

Our results survive a battery of robustness checks, including to the set of inputs used and to how we construct price indices and tariffs. An important remaining concern is unobserved quality and variety changes. If tariff cuts allowed plants to access imported inputs of higher quality (or new varieties of inputs), then this would potentially bias the IV estimation. The most direct channel is through access to higher quality imported inputs. We address this by restricting the sample to plants that never use imported intermediates and confirm that the estimated elasticities remain unchanged. However, tariff reductions could also have led domestic producers to upgrade their quality. To address this last concern, we run simulations to quantify the potential magnitude of unmeasured quality bias and find that our IV estimates would still remain considerably larger than one even when tariff changes induced a large amount of quality upgrading by domestic producers.

India's trade liberalization – while quasi-random – went hand-in-hand with a set of other reforms, including industrial delicensing and FDI liberalization. This raises concerns for both the internal validity of the instrument and the external validity of our elasticity estimates. Regarding internal validity, a correlation between tariff changes and other reforms could lead to an upward bias in our IV estimates. However, we show that there is no economic or statistical difference in tariff changes between reformed and non-reformed industries. Regarding external validity, plants in industries undergoing other reforms might have changed their input mix more following a given price chance since they were already in the process of reorganizing production. To evaluate this, we separately estimate elasticities of substitution in industries that did and did not undergo other reforms. The results do not indicate higher elasticities in sectors with simultaneous reforms, suggesting that the elasticity of substitution we estimate would also prevail in settings where only relative input prices changed.

Our second contribution is to quantify the aggregate importance of intermediate input substitutability. We embed our elasticity estimates in a general equilibrium model with input-output linkages (following Long and Plosser (1983) and Horvath (1998)), heterogeneous firms, and international trade. Firms produce output using labor as well as domestic and imported intermediate inputs from each sector. They have idiosyncratic productivities and face distortions which take the form of a tax or subsidy on revenues. We calibrate the model to match plant-level data from the ASI, markup estimates for Indian manufacturing firms from De Loecker, Goldberg, Khandelwal and Pavcnik (2016), and sector-level data from the World Input-Output Database (WIOD).

We first show that our elasticity estimates imply larger gains from trade in intermediate inputs, coupled with more reallocation of resources. The aggregate consumption gains from India's trade liberalization are 2.2% with a unitary between-materials elasticity and 2.4% with our estimated elasticity – 9% larger. The gains are larger because the trade liberalization led to large relative price changes across material inputs. With high elasticities of substitution, plants can more easily substitute towards the inputs whose relative prices fell. This substitution has important distributional consequences. Qualitatively, the set of sectors who see their workforce shrink and grow is different in a substitutes vs Cobb-Douglas economy. Quantitatively, the overall share of workers who move sectors following the trade liberalization is 40% higher with our estimated elasticity.

In the spirit of development accounting exercises (Hall and Jones, 1999), we quantify the increases in aggregate consumption from closing the India-U.S. TFP gap in each sector. On average, we find gains which are 29% larger relative to Cobb-Douglas, and 42% larger relative to Leontief. The amplification stems from non-linearities in the relationship between sectoral productivity shocks and aggregate consumption. The non-linearities are strong enough to reverse the ordering of sectors in terms of their importance for aggregate output.

Finally, we calculate the costs stemming from plant-specific distortions to input and output prices (à la Hsieh and Klenow (2009)). We find that the aggregate gains from removing all revenue distortions are 15% assuming unitary elasticities, and 18% with our estimated elasticities. We find that distortions which affect the plant-level mix of intermediate inputs such as differences in markups across sectors or idiosyncratic input distortions are much more damaging when substitutability between intermediates is high. The gains from equalizing markups across sectors are three times larger with our estimates relative to Cobb-Douglas – 0.6% vs 0.2%. Similarly, with unitary elasticities, we find losses of 6% from increasing the dispersion of input-specific distortionary taxes, which could for example capture contracting frictions between firms (Boehm, 2022). The losses are 19% - more than three times larger - when using our estimates.

Related Literature There is an extensive literature estimating elasticities of substitution in macroeconomic and trade models.[1] To the best of our knowledge, our paper is the first to estimate long-run elasticities of substitution between different categories of material inputs. This is both due to extensive data requirements and because there are few settings with plausibly exogenous variation in material input prices.[2] Boehm et al. (2019), Barrot and Sauvagnat (2016), and Atalay (2017) estimate short-run elasticities between material inputs in the U.S. using temporary price shocks for identification. They all find estimates close to 0. Existing estimates are important inputs for models focused on short-run horizons, such as Bachmann, Baqaee, Bayer, Kuhn, Löschel, Moll, Peichl, Pittel and Schularick (2022) who evaluate how the German economy would adjust to a stop of energy imports from Russia. Our estimates of long-run elasticities are needed to analyze a different set of questions, such as the long-run effects of permanent shocks, policies and frictions.

Our paper fits into a literature that emphasizes differences between short-run and

[1] Redding and Weinstein (2016) and Hobijn and Nechio (2019) 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, Lelarge and Peters (2019)), capital and labor (Raval (2019); Oberfield and Raval (2021)), and capital/labor and intermediates (Oberfield and Raval (2021), Atalay (2017), Miranda-Pinto and Young (2020), Chan (2017), Doraszelski and Jaumandreu (2018)).

[2] León-Ledesma, McAdam and Willman (2010) discuss the conditions under which elasticities of substitution can be estimated from time-series data on expenditure shares and prices with biased technical change.

long-run adjustments to shocks. Huneeus (2018) and Liu and Tsyvinski (2021) develop models in which firms and sectors may be slow to react to shocks due to adjustment costs — leading to higher long-run relative to short-run elasticities. Ruhl (2008) highlights that shocks of different persistence can also lead to different estimates of short-run vs. long-run trade elasticities. Fitzgerald and Haller (2018) and Boehm, Levchenko and Pandalai-Nayar (2022) use firm and product-level trade data respectively to estimate both short-run and long-run trade elasticities, finding higher elasticities in the long-run. In particular, Boehm et al. (2022) estimate that it takes 7-10 years to converge to the long run. Hurst, Kehoe, Pastorino and Winberry (2022) study the short- and long-run impact of minimum wages — finding larger impacts in the long run as firms are slow to adjust their input mixes.

Our paper also contributes to the macroeconomics and trade literatures on intersectoral linkages. Due to the lack of empirical evidence suggesting otherwise, the prevailing assumption in this literature is Cobb-Douglas production – firms or sectors do not change their spending shares when input prices change (Caliendo and Parro (2015); Bartelme and Gorodnichenko (2015); Acemoglu, Carvalho, Ozdaglar and Tahbaz-Salehi (2012)). Recent exceptions include Baqaee and Farhi (2019, 2020a,b) who derive second-order approximations for the aggregate impact of business cycle shocks, the impact of distortions, and changes in trade barriers. Jones (2011) examines the role of complementarities between intermediate inputs in explaining cross-country differences in development. Since we estimate that inputs are substitutes rather than complements, we find – contrary to Jones (2011) – that productivity changes in one sector can indeed have large consequences for aggregate output.[3]

Finally, our paper builds on a considerable literature examining the effects of India's trade liberalization on various economic outcomes including poverty (Topalova (2010)), productivity and reallocation (Krishna and Mitra (1998); Sivadasan (2009); Topalova and Khandelwal (2011)), product range (Goldberg, Khandelwal, Pavcnik and Topalova (2010)) and markups (De Loecker et al. (2016)). It also relates to a broader literature evaluating the gains from trade in intermediate inputs (Amiti and Konings (2007), Blaum et al. (2019), Caliendo and Parro (2015), Ossa (2015) and Tintelnot, Kikkawa, Mogstad and Dhyne (Forthcoming)); and in particular Oberfield and Boehm (2020) who analyze the importance of input linkages between Indian manufacturing firms, focusing primarily on the effect of contractual frictions.

[3]Other recent contributions to the literature incorporating frictions in macroeconomic models with production networks include Bigio and La'O (Forthcoming), Caliendo, Parro and Tsyvinski (Forthcoming), Altinoglu (Forthcoming), Baqaee (2018), Baqaee and Farhi (2020b), Liu (2019) and Osotimehin and Popov (2020).

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

2. Estimating Equations

Our goal is to estimate the causal response of plant intermediate input use to changes in input prices at different levels of aggregation. The first level of aggregation we consider is between broad categories of material inputs. We estimate how spending shares on a given material input k relative to input j change in response to changes in the relative prices of k and j. Consider the following log-linear specification:

$$\Delta\ln\left(\frac{PM_{ik}}{PM_{ij}}\right) = \alpha_m + \beta_m \Delta\ln\left(\frac{P_{ik}}{P_{ij}}\right) + \epsilon_i \tag{1}$$

where $\Delta\ln\left(\frac{PM_{ik}}{PM_{ij}}\right)$ is the log change in plant i's relative expenditure share on material inputs k and j; and $\Delta\ln\left(\frac{P_{ik}}{P_{ij}}\right)$ is the log change in plant i's relative price for materials k and j.

With exogenous variation in input prices, the coefficient β_m in Equation (1) identifies the local elasticity of substitution between material inputs k and j. When elasticities are independent of the magnitude of the price change, such as in a standard CES framework, this data moment exactly identifies *the* elasticity of substitution between material inputs. At higher levels of aggregation, the causal relationship between spending on all materials relative to all energy or services inputs and their relative prices similarly identifies the elasticity of substitution between energy, materials, and services. Furthermore, the elasticity of substitution between intermediate inputs and value-added – the bundle of capital and labor – is identified by changes in spending on intermediate inputs induced by changes in the price of these inputs relative to the price of capital and labor.

To nest all these elasticities, we consider a production function for plant i in period t which takes the following 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 bundle $F(L_{it}, K_{it})$ and an intermediate input bundle X_{it}. ε is the elasticity of substitution between the capital-labor bundle and the intermediate input bundle. γ_{it} determines the relative importance of value-added in production. The intermediate input bundle X_{it} has a nested CES structure. Consistent with the KLEMS approach to national accounting, the upper nest consists of energy (E_{it}), materials (M_{it}), and services (S_{it}):

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

θ^X 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. In particular, M_{it} is given by:

$$M_{it} = \left[\sum_{k=1}^{K^m} \pi_{ikt}^{m} M_{ikt}^{\frac{\theta - 1}{\theta}}\right]^{\frac{\theta}{\theta - 1}}$$

θ is the elasticity of substitution between the K^M different types of material inputs, such as metals and plastics. The plant-specific technologies π_{ikt}^{m} determine the relative importance of each type material input in production. These could reflect different production 'recipes' as in Oberfield and Boehm (2020).[4]

To derive our estimating equations, we only need to assume that plants minimize costs, taking input prices as given. We impose no assumptions on the demand structure and allow input prices to vary across plants.[5] From the firm's first-order conditions and taking changes over time, we have that:

$$\Delta\ln\left(\frac{PM_{ik}}{PM_i}\right) = (1-\theta)\Delta\ln\left(\frac{P_{ik}}{P_i^m}\right) + \theta\Delta\ln(\pi_{ik}^{m}) \tag{2}$$

Equation 2 is the structural equation we take to the data. In the Cobb-Douglas benchmark, $\theta = 1$ and expenditure share changes are independent of price changes. If price increases cause a decrease in expenditure shares however, this is a sign of high substitutability. We derive similar equations for θ^X and ε.

Estimating these parameters requires data on plant-level intermediate input expenditures and on input prices, as well as plausibly exogenous variation in input prices. OLS estimates are likely to be biased and inconsistent for two main reasons. Firstly, changes in production technologies (π_{ki}^{m}) may drive changes in prices, creating a simultaneity bias. Secondly, measurement error in input prices may create attenuation bias. Our estimation strategy therefore involves using changes in import tariffs during India's trade

[4] Because π_{ikt}^{m} can equal 0, our notation allows for extensive margin differences in the set of inputs used across plants.

[5] Input prices may vary because plants use different bundles of inputs within M_{ikt}.

liberalization as an instrumental variable when estimating these equations in 2SLS. We describe key features of the trade liberalization and why it is an ideal policy experiment for identification next.

3. Empirical Setting and Data

In this section we first provide details regarding India's trade liberalization, which we argue is an ideal natural experiment in which to estimate the elasticities of substitution between intermediate inputs. We then provide more details about the datasets used in the estimation.

3.1. India's Trade Liberalization

Following its independence in 1947, India's government imposed strict controls and restrictions on the manufacture of goods. These industrial policies involved licensing restrictions, FDI restrictions and high import tariffs as well as non-tariff barriers.[6] While some restrictions started to be gradually relaxed during the 1980s, India still remained a very closed economy in 1990, with average import tariffs around 80%. However, due to rising macroeconomic imbalances throughout the 1980s, the rise in the price of oil and drop in remittances following the first Gulf War triggered a balance of payments crisis in 1991. The Indian government therefore arranged a Stand-By Arrangement with the International Monetary Fund, which was conditional on a program of major structural reforms.

An important component of these reforms was trade liberalization, which was implemented as part of India's Eighth Five-Year Plan between 1992 and 1997. Figure 1a shows that average Indian import tariffs declined from 80% down to 30% between 1991 and 1997.[7] There was also a dramatic reduction in tariff dispersion. Initial tariff levels in 1991 were highly heterogeneous across goods, and tariff harmonization was a goal of the reform. As shown in Figure 1b, the initial level of a tariff is an excellent predictor of its change during the reform. Non-tariff barriers on intermediates inputs were also reduced rapidly in the first few years of the trade liberalization, and remained high only for a small subset of agricultural products.

Because of the sudden and unexpected nature of the crisis, the trade liberalization

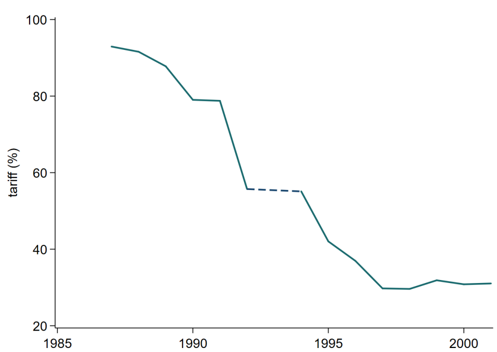
[6] See Panagariya (2004) and Sivadasan (2009) for an extensive list of India's industrial policies.

[7] Our dataset of Indian import tariffs at the HS6 product code level is the same as that used in Topalova (2010) and Topalova and Khandelwal (2011). We are very grateful to the authors for sharing their data with us.

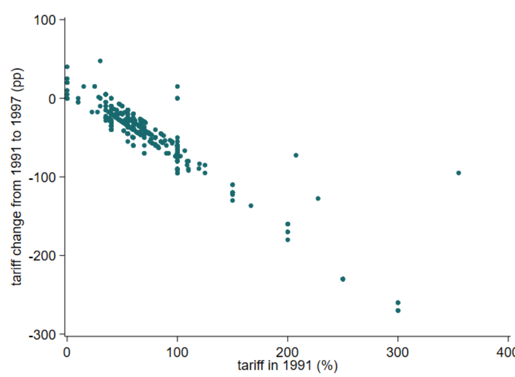
was pushed through rapidly and without much scope for industry lobbying.[8] Topalova (2010) and Topalova and Khandelwal (2011) show that pre-reform industry characteristics and trends do not predict tariff changes between 1991 and 1997. We confirm these findings in Table B.2. Gang and Pandey (1996) suggest that this was due to trade policy hysteresis; Indian trade policy was determined during the Second Five Year Plan (1956-1961) and didn't change even as the structure of industry evolved. We also show in Appendix B1. that tariff changes were also not correlated with the other reforms that occurred in 1991, in particular FDI reform and industrial delicensing. Figure B.1 shows that the distribution of tariff changes between 1991 and 1997 is very similar for industries that did and didn't experience other reforms, with the difference in average tariffs both small and statistically insignificant.

Figure 1: Indian Import Tariffs

(a) Average Indian Import Tariffs



(b) Tariff Changes vs Levels

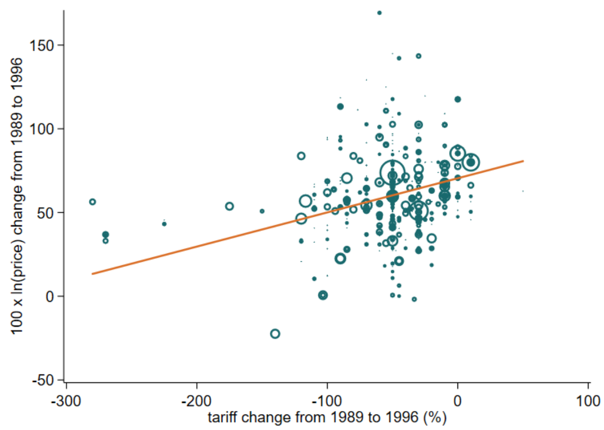


Notes: sub-figure (a) shows average Indian import tariffs between 1988 and 2002. We construct average tariffs as the unweighted average of HS4-level tariffs. We omit 1993 because of measurement error concerns. Sub-figure (b) plots the percentage point change in Indian import tariffs between 1991 and 1997 against the level of import tariffs in 1991. Each dot corresponds to a HS4 product category. The R-squared from a regression of tariff changes on initial tariff levels is 0.85. We use data on Indian import tariffs from Topalova (2010) for both figures.

A second important feature of India's trade liberalization is that there was considerable dispersion in tariff changes (Figure 1b), which in turn lead to large changes in the relative domestic prices of Indian goods. In Figure 2 we illustrate these pro-competitive effects of India's trade liberalization in the aggregate price and tariff data (we use domes-

[8]This point is argued in Hasan, Devashish and Ramaswamy (2003), Goyal (1996) and Varshney (2000). There is also strong anecdotal evidence of this. Dr. 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 [...]. We didn't have the time to sit down and think exactly what kind of a development model we needed'* (Topalova (2010), with full interview available here: https://www.rediff.com/money/2004/jul/05inter.htm)

Figure 2: Pro-Competitive Effects of Tariff Reductions



Notes: This figure plots the change in Indian domestic wholesale prices against the change in Indian import tariffs between 1989 and 1996; see Sections 3.2.2. for details on data sources and construction. Each point corresponds to a 5-digit ASICC product category, weighted according to its share in total manufacturing material expenditures in 1996 (as measured in the ASI, see Section 3.2.1.). We also plot the fitted line from the weighted linear regression. This line has slope = 0.212 and robust standard error = 0.054.

tic price data from India's Wholesale Price Index).[9] Inputs which experienced larger tariff declines also experienced larger relative price declines. As shown in De Loecker et al. (2016), declines in firm markups are an important explanation for these pro-competitive effects. We use these tariff-induced changes in relative domestic prices as the source of variation which identifies the elasticity of substitution between different types of material inputs.[10]

3.2. Datasets

In order to estimate Equation 2, we need data on input expenditures of Indian plants over time, as well as on the prices they face for these inputs. We also need to match the tariff declines, which we use as instruments, to price changes. This section describes the main datasets we use.

[9]We discuss construction of the WPI in more detail in Section 3.2.2.

[10]An alternative approach would have been to use changes in domestic prices induced by lower *input* tariffs as our source of variation. However, we find a relatively weak relationship between domestic prices and input tariffs. De Loecker et al. (2016) find a similar result and show that this weak relationship is due to imperfect pass-through of marginal costs to prices because of increasing markups.

3.2.1. Annual Survey of Industries

We use the Indian Annual Survey of Industries (ASI) for plant-level data on intermediate input expenditures. The ASI is a nationally representative survey of registered (formal) Indian manufacturing plants. Plants with more than 100 workers are surveyed every year, while plants with more than 10 workers are randomly sampled. The survey contains many of the standard measures of output (sales, inventories) and inputs (labor, capital, materials).

The main variables we use from the ASI are plant-level expenditures on material inputs, fuel inputs, and service inputs. A strength of the ASI is that plants report these expenditures for narrowly defined categories.[11] Imports and domestic material expenditures are reported separately. We use the 1989 and 1996 ASI surveys for pre-reform and post-reform plant-level data (see Appendix A1. for more details). We use linking factors from a previous release of the ASI to construct a panel (see Bils, Klenow and Ruane (2021) and Alcott, Collard-Wexler and O'Connell (2016)). Summary statistics and the employment distribution of plants are shown in Appendix Table A.1 and Figure A.1.

In 1996, plants report values and quantities of their material input consumption according to the Annual Survey of Industries Commodities Classification (ASICC). The ASICC classifies all materials into 9 different 1-digit categories: '1. Animal and Vegetable Products', '2. Ores and Minerals', '3. Chemicals', '4. Rubber, Plastics and Leather', '5. Wood, Cork and Paper', '6. Textiles', '7. Metals', '8. Transport Equipment' and '9. Other Manufactured Articles'.[12] These are further disaggregated into 250 3-digit categories and 5500 5-digit categories. In 1989, plants report their materials according to the ASI Item Code classification. To link plants' input usage over time, we construct a concordance between the ASI Item Code classification and the ASICC at the 5-digit and 3-digit level (see Table A.5). Table A.2 shows the most commonly used material inputs within each 1-digit category, examples of which include gunny bags, sulphur and ball bearings. In addition, Appendix A2. provides detailed summary statistics about the data.

3.2.2. Domestic Prices and Tariffs

We use prices for domestically produced inputs from India's Wholesale Price Index (WPI) which is constructed by India's Office of the Economic Advisor. It measures yearly prices for 450 goods. The WPI is a good measure of domestic input prices for two main reasons. First, its scope is large. While having broad coverage of the main agricultural and mining commodities, it is also designed to cover all manufactured products with traded values

[11] Prowess, another commonly used dataset of Indian firms, only contains information about total expenditures on materials, fuels, and services.

[12] In practice, we drop the 1-digit ASICC category '8. Transport Equipment' in the analysis because it is comprised almost exclusively of capital goods and is rarely reported in the materials section of the ASI survey.

above Rs 120 crore ($\approx$ 16 million USD). Second, according to the documentation, statistical authorities were well aware of issues related to quality and variety changes over time and designed the WPI to track goods of constant quality.[13]

Despite attempts by authorities to address these issues, it is well known that variety and quality biases continue to complicate inflation measurement even in the U.S. (Boskin, Dullberger, Gordon, Griliches and Jorgenson (1996)). We discuss how these could affect our estimation strategy in Section 4.. We complement the WPI with service and fuel price indices from World KLEMS.

We use official Indian import tariffs from Topalova (2010). These are available for 5000 HS6 good categories. We construct a concordance linking our price and tariff data to the ASICC classification at the 5-digit level (see A.6). We obtain price and tariff measures for close to 600 5-digit ASICC categories. As Figure 2 shows, there is considerable dispersion in aggregate price and tariff changes across inputs.

4. Estimation

In this section we first describe the estimation of the plant-level elasticity of substitution between 1-digit materials. We then describe the estimation of higher-nest plant-level elasticities; between energy, materials and services, and between intermediates and value-added. We lastly estimate these elasticities at the industry-level.

4.1. Elasticity Across 1-digit Materials: θ

4.1.1. Baseline Specification

Our empirical strategy follows from equation (2). We use the following specification to estimate the elasticity of substitution between eight 1-digit material input categories:

$$\text{First stage: } \Delta\ln(P_{ik}) = \rho_m \, \Delta\tau_{ik} + \lambda_i + \lambda_k + \eta_{ik} \tag{3}$$

$$\text{Second stage: } \Delta\ln\left(\frac{PM_{ik}}{PM_i}\right) = \beta_m \, \Delta\ln(P_{ik}) + \lambda_i + \lambda_k + \epsilon_{ik} \tag{4}$$

where i denotes a plant, k a material input category (e.g. Textiles), and Δ stands for changes between 1989 and 1996. PM_{ik}/PM_i are expenditures by plant i on material input k as a share of total material expenditures. $\Delta\ln(P_{ik})$ is the change in plant i's Tornqvist price index for material input k. τ_{ik} is an import tariff measure for plant i's material

[13] See https://eaindustry.nic.in/archive_data/archive/wpi_technical_report.pdf for additional details on the data collection and construction of the price index.

input k. λ_i is a plant fixed effect which controls for changes in plant i's material price index (P_i^m in equation (2)) as well as total plant material expenditures. λ_k is a material input fixed effect which absorbs any common trends in input prices and spending shares for material k. ρ_m is the elasticity of domestic input prices with respect to import tariffs; the pro-competitive effects of tariff reductions. β_m is the estimate of one minus the elasticity of substitution between materials.

We construct $\Delta\ln(P_{ik})$ as the expenditure-share weighted average change in 5-digit material input prices used by plant i. We use Tornqvist expenditure share weights; averages between 1989 and 1996. $\Delta\ln(P_{ik})$ is therefore a second order approximation to the change in the price index for any constant elasticity between 5-digit inputs. We construct the tariff instrument using the same approach as for prices, except we weight the 5-digit ASICC tariff changes with 1989 expenditure shares rather than Tornqvist shares.[14] These variables are constructed as shown in equations (5) and (6), where l is a sub-category of material inputs.[15]

$$\Delta\ln(P_{ik}) = \sum_l \frac{1}{2}\left(w_{ikl,96} + w_{ikl,89}\right)\Delta\ln(P_{kl}) \tag{5}$$

$$\Delta\tau_{ik} = \sum_l w_{ikl,89}\Delta\tau_{kl} \tag{6}$$

The estimation sample consists of plants we observe in the ASI in both 1989 and 1996 and which use at least two categories of material inputs in both years.[16] The latter restriction comes from the fact that our specification identifies $\hat{\theta}$ from changes in relative expenditure shares: e.g. we need to see a plant with expenditures on 'Metals' as well as 'Rubber, Plastics and Leather' in both years.[17] We trim the 1% tails of spending share changes and price changes, as well as the 5% tail of tariff changes. We choose a higher cut-off for tariff changes, since their distribution is left-skewed and these outliers can have a disproportionate weight in the IV estimation.[18] Table 1 shows summary statis-

[14] We use 1989 rather than Tornqvist shares to avoid construct the instrument using post-liberalization plant expenditures.

[15] In practice, we first aggregate 5-digit price indices and tariffs to the 3-digit level using plant spending shares when possible. When we observe plant spending shares at the 3-digit level, but not for the 5-digit sub-components (due to incomplete concordances), we use aggregate 5-digit spending shares to construct the plant-level 3-digit price indices. We then always aggregate 3-digit prices and tariffs to the 1-digit level using plant spending shares.

[16] In addition, we restrict the sample to plants who stay in the same 4-digit industry; i.e. did not change their main production activity.

[17] In practice, there is very little change in the set of 1-digit inputs used by plants across the two years. At this level of aggregation, the median value-share of dropped/added inputs is 0.6%.

[18] This sets the largest tariff decline to -160pp. In contrast to tariff changes, the distribution of price changes and spending share changes is symmetric. We report even larger IV estimates without this trimming of the left tail of tariff changes in the Appendix. We also show that our results are similar for different approaches to data cleaning in our robustness checks.

tics for the resulting estimation sample, which consists of 13,275 observations and 5,150 plants. Summary statistics for the full and panel samples are reported in Appendix Table A.1.

Table 1: Summary Statistics

Variable	Mean	Std. Dev.	P1	P10	P90	P99
Δln(spending share)	0.00	1.07	-3.32	-1.10	1.16	3.33
Δln(price)	0.60	0.15	0.28	0.41	0.77	1.00
Δtariff	-0.59	0.30	-1.38	-1.10	-0.30	-0.10

Notes: The table contains summary statistics for main variables used in the estimation of θ. We restrict the set of inputs to those that account for at least 0.1% of plant material expenditures on average. We trim the 1% tails of spending share changes and price changes, as well as the 5% tail of tariff changes. We choose a higher cut-off for trimming for tariff changes, since their distribution is left-skewed and these outliers can have a disproportionate weight in the IV estimation. There are 13,275 observations and 5,150 plants in the final estimation sample.

4.1.2. Identification

OLS estimates of elasticities of substitution might suffer from attenuation bias as well as simultaneity bias. Measurement error in input prices biases $\hat{\beta}_m$ towards 0, thereby biasing $\hat{\theta}$ towards 1. Simultaneity bias could arise for instance from structural shifts in the demand for materials. For example, the adoption of a new cotton-intensive weaving machine might increase the demand for cotton, and thereby lead to an increase in both the expenditure share on cotton and the price of cotton – the latter will be true as long as the supply curve of cotton is upward sloping. The resulting positive correlation between prices and expenditure shares will bias OLS estimates of θ towards 0. We overcome both of these concerns by instrumenting price changes with tariff changes.

We construct the instrument for domestic input prices by aggregating national-level tariff changes using plant-specific expenditure shares. This is therefore a Bartik (1991) instrument. The inclusion restriction is that changes in import tariffs affect domestic prices. This strong relationship can be seen in the national level data in Figure 2 and is also clear in our first stage regression in Table 2.

Our identifying assumption is that the variation in tariffs across 5-digit ASICC inputs is quasi-random. Borusyak, Hull and Jaravel (2022) show that for Bartik instruments, quasi-randomness of the aggregate shocks is a sufficient condition for identification, provided that the shocks are dispersed and large in number, and with sufficiently small average exposure.[19] Figure 2 shows that these conditions are met in our setting: There is

[19]Note that our identification strategy does not require that the 1989 plant expenditure shares be quasi-randomly distributed. Random assignment of plant spending shares is a sufficient condition (as shown in Goldsmith-Pinkham, Sorkin and Swift (2020)), though not a necessary one.

a lot of dispersion in tariff changes across the large number of 5-digit ASICC categories (563), and plant-level exposures to each individual tariff changes (given by their share of aggregate expenditure in 1996) is small on average.

As discussed in Section 3.1., tariff changes during India's trade liberalization were arguably quasi-random. Consistent with this argument, Topalova and Khandelwal (2011) show that tariff changes between 1991 and 1997 are uncorrelated with industry characteristics in the pre-reform period. In Table B.2 we confirm their findings by documenting that neither industry characteristics in 1988 (such as size or capital intensity) nor industry trends between 1985 and 1988 (in prices, size or TFP) are correlated with changes in input or output tariffs between 1989 and 1996.

Finally, one might be concerned that the tariff changes happened to be correlated with other reforms that occurred in India during the same period. After all, India also reformed its FDI policies and delicensed many industries. We obtain measures of both of these at the 3-digit industry level from Aghion, Burgess, Redding and Zilibotti (2008) and show in Figure B.1 that neither of these simultaneous reforms were correlated with tariff changes. There is no significant difference in tariff changes between industries that were vs. were not delicensed in 1991, and industries that did vs. did not undergo FDI reform.

4.1.3. Estimation Results

Table 2 presents the baseline estimation results. We estimate that a 10 pp reduction in tariffs reduces domestic prices by 1.28%. Reassuringly, this is similar to De Loecker et al. (2016) who find an impact on prices of 1.56% using a different measure of prices from Prowess and pooling together all years between 1989 and 1997. The first stage is strong, with an F-statistic of 63.3, well above the conventional threshold of 10. Our OLS estimate of θ is 1.4 with a 95% confidence interval lying above 1. This is already a striking result, given that both attenuation bias and simultaneity bias should lead to downward biased estimates of θ.[20] Consistent with this, the IV estimate is six times larger than the OLS estimate, implying an elasticity of 3.1 with a 95% confidence interval of [1.84, 4.37].

Our results provide strong evidence that the medium to long-run elasticity of substitution between different categories of materials is significantly above 1. This contrasts with existing short-run estimates in the literature which have tended to find elasticities near zero (Barrot and Sauvagnat, 2016; Atalay, 2017; Boehm et al., 2019). To interpret the magnitude of the IV coefficient, consider a plant that uses two inputs, each with an initial spending share of 50%. The IV estimate implies that a 10% change in relative prices

[20] In addition, the OLS estimates could be picking up short-run changes in prices as well as the long-run changes induced by tariff reforms. To the extent that short-run elasticities of substitution are lower, this would provide an additional source of downward bias in the OLS estimates.

Table 2: Baseline estimates of θ

	OLS	IV
Δln(prices)	-0.352	-2.107
	(0.154)	(0.643)
Implied $\hat{\theta}$	1.352	3.107
	[1.05, 1.65]	[1.84, 4.37]
		First Stage
Δ tariffs		0.128
		(.016)
F-stat		63.3
Observations	13,275	13,275
# plants	5,150	5,150

Notes: This table shows our estimation results from the specifications shown in equations 3 and 4. The dependent variable in the OLS and IV specifications are the change in plant spending shares between 1989 and 1996. The dependent variable in the first stage is the change in material input prices. An observation is a plant $\times$ 1-digit material input category. All regressions include plant fixed effects and 1-digit material category fixed effects. Regressions are weighted by the inverse of the number of inputs used by the plant; each plant is weighted equally. Standard errors are clustered at the 4-digit industry level.

will lead to the relatively more expensive input's share declining to 45.0% over time, and the relatively cheaper input's share increasing to 55.0%.[21]

4.1.4. Robustness

Our empirical estimates are robust to a variety of checks shown in Table 3 and in the Appendix Table B.3. The baseline specification does not restrict the number of inputs used by the plant. In principle, the high substitutability we find could be driven by changes in spending on inputs with very low average expenditure shares. We show in columns (1) and (2) of Table 3 that our results are similar when restricting the sample to only the three inputs with the highest (average) value share for each plant.

Plants could also adjust their input mix at the extensive margin, for example dropping cardboard/paper containers entirely and switching to plastic. These extensive

[21] For an input with an initial spending share of 10%, a 10% increase in its relative price would lower its spending share to 8.3%.

Table 3: Robustness of θ Estimates

	Top 3 Inputs		No Extensive Margin		Industry Prices and Tariffs		Non-importers	
	OLS	IV	OLS	IV	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Δln(prices)	-0.384	-2.027	-0.380	-2.150	-0.272	-1.531	-0.390	-2.249
	(0.159)	(0.660)	(0.234)	(0.953)	(0.153)	(1.076)	(0.191)	(0.734)
Elasticity	1.384	3.027	1.380	3.150	1.272	2.531	1.390	3.249
	[1.07, 1.70]	[1.73, 4.32]	[0.92, 1.84]	[1.27, 5.03]	[0.97, 1.57]	[0.42, 4.64]	[1.01, 1.77]	[1.80, 4.69]
		First Stage		First Stage		First Stage		First Stage
Δtariffs		0.129		0.115		0.126		0.126
		(.017)		(.016)		(.027)		(.020)
F-stat		59.8		50.6		21.6		41.8
Observations	12,439	12,439	4,083	4,083	13,275	13,275	10,121	10,121
# plants	5,150	5,150	1,505	1,505	5,150	5,150	3,942	3,942

Notes: This table shows our estimation results under various robustness specifications. The dependent variable in the OLS and IV specifications are the change in plant spending shares between 1989 and 1996. The dependent variable in the first stage is the change in material input prices between 1989 and 1996. An observation is a plant $\times$ 1-digit material input category. Standard errors are clustered at the 4-digit industry level. All regressions include plant fixed effects and 1-digit material category fixed effects. Regressions are weighted by the inverse of the number of inputs used by the plant. The 'Top 3 Inputs' specification restricts the sample to the three most important inputs per plant, as measured by each input's average expenditure share. The 'No Extensive Margin' specification restricts the sample to plants who use report using exactly the same set of 1-digit inputs in 1989 and in 1996. The 'Industry Prices and Tariffs' specification uses price and tariff variables constructed using average industry value shares instead of plant-specific value shares. The 'Non-importers' specification restricts the sample to plants that don't import in either 1989 or 1996.

margin adjustments are not captured in our estimation, and we may therefore be understating substitution for plants where this extensive margin is important. To evaluate the potential importance of this, we report in columns (3) and (4) that our results very similar when restricting the sample to plants that have no extensive margin input adjustment at the 1-digit level.

Finally, a concern is that using 1989 plant expenditure shares to construct the instrument creates a mechanical correlation between the instrument and the second stage structural residual. In columns (5) and (6), we show that we get similar results when we use average industry value shares to construct the price and tariff variables. Since this specification uses less variation in the data, the resulting estimates are less precise.

In Table B.3 we provide additional robustness checks. We show that our results are robust to the way we clean and trim the data, and alternative methods of constructing price indices and tariff measures.[22] To alleviate the possible concern that our results are affected by an incomplete concordance from the 1989 to the 1996 input classification,

[22]The most notable difference is if we do not trim the 5% left tail of tariff changes. In this case, we estimate an even higher elasticity of substitution of 4.7.

we re-run our estimation for the subset of plants where more than 95% of inputs in 1989 are concorded to the 1996 ASICC classification. We find very similar results to our baseline. Lastly, we cluster our standard errors at the input by 2-digit industry level, rather than the 4-digit industry level. This allows for plants in the same broad sector to face correlated price shocks because they use similar input mixes. The standard error of the IV estimate increases moderately from 0.64 to 0.80.

4.1.5. Quality Upgrading.

As discussed in Section 3.2.2., the input price data we use in the estimation was constructed to track goods of constant quality. Despite this, one might worry that there are residual unmeasured changes in the quality of goods for which prices were collected, and that these might complicate the estimation.[23] In the OLS estimation, unmeasured quality changes act like classical measurement error. To illustrate this, suppose that the quality of input k increased. The quality increase leads to an increase in the measured nominal price of that input, even though the true, or quality-adjusted, price remains constant. Since there was no effective price change, firms do not adjust their input mix and their expenditure share on input k is unchanged. However, the *measured* price increased, which would lead an econometrician to erroneously estimate an elasticity of substitution of 1. As previously discussed, this type of measurement error is one of the potential reasons why the OLS estimate of θ is biased towards 1.

The IV deals with this source of bias from unobserved quality changes, but potentially adds an additional concern. If the trade liberalization made imported inputs of higher quality available (Goldberg et al., 2010), then we risk mis-measuring the true input price changes for firms who import intermediate inputs. This is due to the fact that we use domestic input prices only, as we are not aware of quality adjusted import prices at the good level. Since the potential for mis-measuring quality changes of imports is higher in industries that saw larger tariff declines, this could introduce a bias in the IV estimation. To alleviate this concern, we re-run our estimation on the sub-sample of plants that only use domestic intermediate inputs throughout the sample period. Changes in the quality of imported intermediates are then by construction not an issue for these plants and we are correctly measuring prices. As columns (7) and (8) of Table 3 show, our estimates are robust to this.

The final concern we address is that reductions in import tariffs may induce domestic producers to improve the quality of their products (Verhoogen, 2008; Bas and Strauss-Kahn, 2015). To the extent that these quality changes are not perfectly captured

[23] In a similar way, the introduction of new varieties – if unmeasured – would lead to us to understate price changes. This channel introduces the same concerns as unmeasured quality changes for a constant basket of goods. For ease of exposition, we refer to quality only for the remainder of the discussion.

by the Wholesale Price Index, they might introduce a bias in the IV estimates. We evaluate the potential direction and magnitude of this bias in Appendix B2.. We show that, if tariff reductions induce quality upgrading, this would result in our IV estimate being upward biased. Using simulated regressions, we quantify the potential magnitude of this bias. We find that if the unmeasured quality response to tariffs amounts to 10% of the observed price response, the true elasticity of substitution would be 2.9, declining to 2.4 if the unmeasured quality upgrades are as high as 50% of observed price responses.[24] These results suggest that, even for very large unmeasured quality changes induced by tariff changes, the true elasticity of substitution remains high.

4.1.6. Heterogeneity

The baseline estimation pools together all manufacturing plants and material input categories. However, these estimates potentially mask important heterogeneity across industries and across types of plants. Figure 3 plots both the OLS and IV estimates of θ for each 'using' 2-digit industry.[25] Standard errors are considerably larger given that we are dividing the sample by 20. However, both OLS and IV estimates of θ tend to be greater than 1 for most industries.

We also explore whether plant size is an important source of heterogeneity for our elasticity estimates. Plants of different sizes could have different elasticities of substitution for several reasons. On the one hand, production flexibility could be a sign of good management and therefore correlated with productivity and size. On the other hand, large plants could face larger adjustment costs making it more difficult to change their input mix. Large plants might also produce a broader array of products and use a wider range of inputs, enabling substitution both between inputs and between products. We explore this directly by estimating θ separately for small and large plants. We show the results in Table 4. We find that smaller plants in fact have slightly lower elasticities than larger plants, 3.0 vs. 3.2. Both however are significantly greater than 1.

4.1.7. Discussion of estimated elasticities.

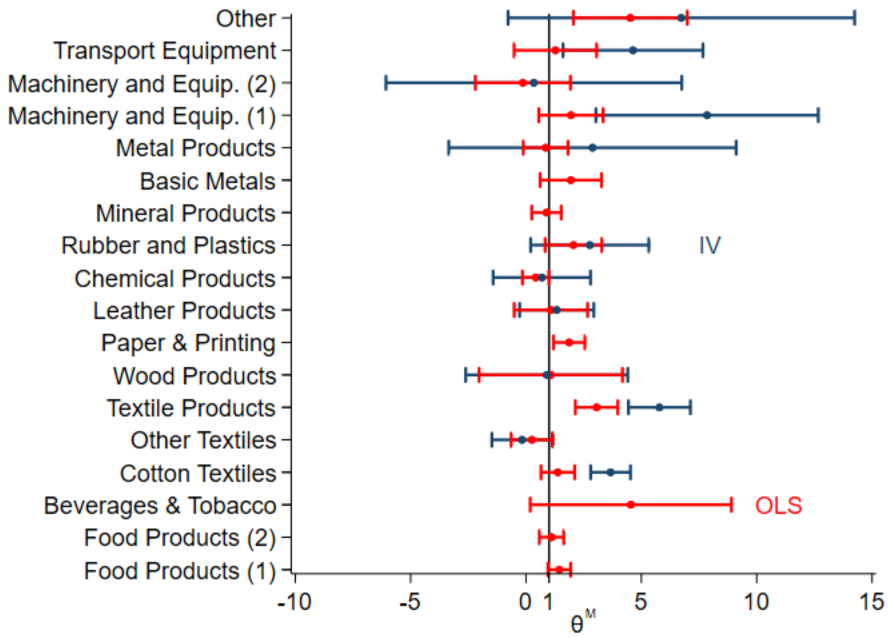
Our results contrast significantly with existing estimates of elasticities at similar levels of aggregation, but identified using business cycle fluctuations in prices (Atalay, 2017). There are three possible reasons for this difference.

First, to the extent that there are adjustment costs or fixed costs to changing one's

[24] Even if the true change in quality-adjusted prices induced by the trade liberalization was twice as large as the change in prices measured by the Wholesale Price Index, the elasticity of substitution is still larger than one, at 2.1.

[25] The estimates are obtained by running equations (3) and (4) for each 2-digit industry after having residualized each variable on both plant and material input fixed effects.

Figure 3: θ heterogeneity: 2-digit industries



Notes: This figure plots the OLS (red) and IV (blue) point estimates of θ with 95% confidence intervals for each using 2-digit NIC industry. The estimation procedure follows the specification in equations (3) and (4). All variables are first residualized on plant and input fixed effects before the estimation is run separately for each industry. Two industries are omitted because of insufficient observations. For six industries with very weak first stage estimates we only report OLS results.

input mix, plants might react differently to a shock that is perceived to be temporary, relative to the permanent changes in prices we exploit. Consistent with 'putty-clay' models of production, plants may optimally not adjust how they organize production in response to transitory price fluctuations, but may be willing to make more substantial changes if price changes are permanent.

Second, it might take time for firms to adjust their input mix. They might have long-term contracts with suppliers that are hard to change in the short-run, or changing the input mix might require reorganization within the plant.[26] Unfortunately, India's trade liberalization is not a setting that allows us to estimate short-run elasticities of substitution, as tariff reductions were announced at the start, but only introduced gradually over time (Figure 1). The estimation of elasticities is therefore less clean at shorter time horizons because of anticipation effects; firms might have started adjusting their input mix in the short-run to *expected* tariff changes which hadn't yet occurred. We therefore restrict our attention in this paper to the estimation of long-run elasticities of substitution between 1989 and 1996.

[26] Huneeus (2018) and Liu and Tsyvinski (2021) propose models of production networks with adjustment costs that results in larger long-run compared to short-run elasticities of substitution.

Table 4: θ heterogeneity by plant size

	Below Median Size		Above Median Size	
	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)
Δln(prices)	-0.409	-2.013	-0.306	-2.186
	(0.211)	(0.858)	(0.189)	(0.847)
Elasticity	1.409	3.013	1.289	3.186
	[1.05, 1.49]	[1.32, 4.7]	[1.07, 1.46]	[1.52, 4.85]
		First Stage		First Stage
Δtariffs		0.136		0.122
		(.025)		(.014)
F-stat		29.87		71.7
Observations	6,436	6,436	6,839	6,839
# plants	2,575	2,575	2,575	2,575

Notes: This table shows our estimation results restricting the sample to plants below or above median size. Our measure of size is plant material expenditures. The dependent variable in the OLS and IV specifications are the change in plant spending shares between 1989 and 1996. The dependent variable in the first stage is the change in material input prices between 1989 and 1996. An observation is a plant $\times$ 1-digit material input category. Standard errors are clustered at the 4-digit industry level. All regressions include plant fixed effects and 1-digit material category fixed effects. All variables are residualized before the sample is split. Regressions are weighted by the inverse of the number of inputs used by the plant.

Third, the fact that we estimate high elasticities of substitution between intermediate inputs could also reflect plants changing their product mix. We restrict the baseline estimation sample to plants who stay in the same industry throughout the liberalization (e.g. manufacture of woolen carpets), however we can't rule out the possibility of product changes within these narrow industries (e.g. colored vs. plain woolen carpets). Since the product classification used by the ASI was overhauled between 1989 and 1996, we cannot directly test this hypothesis. When conducting counterfactuals in a quantitative model in Section 6., we consider an alternative environment in which product-level relative input usage is fixed (Leontief), but firms can adapt by switching across products. When calibrated to fit the same elasticity of total plant input spending with respect to price, the two versions of the model yield quantitatively similar results.

Given that India underwent several reforms starting in 1991, our estimates of a high elasticity of substitution between materials might be specific to the time period in which we estimate them. We already showed that both industrial delicensing and FDI reforms were uncorrelated with tariff changes. Still, if plants were already planning to reorganize their production following these simultaneous reforms, they may have been more likely to also substitute to different inputs as a result of price changes.[27] While this wouldn't invalidate our estimation approach, it may suggest that our estimates would not be externally valid in other settings.

To test whether this is the case, we estimate the elasticity separately for industries which underwent other reforms between 1991 and 1997 and those that didn't. As before, we consider two of the other major sets of reforms which occurred during this period; industrial delicensing reforms and FDI reforms. Reassuringly, we show in Table 5 that elasticities for plants in industries that did not undergo simultaneous reforms are statistically indistinguishable from the ones for plants that did; if anything, the point estimates are larger. This suggests that our estimates would also prevail in other empirical settings where plants only faced changes in relative prices.

4.2. Elasticities between KLEMS Inputs

We now turn to estimating the elasticities governing the two upper nests of our CES production function: between energy, materials, and services and between value added and the bundle of intermediate inputs.

4.2.1. Specification

Analogous to the elasticity between materials, we estimate the the elasticity of substitution between materials and energy from changes in spending shares. We use the following estimating equations (the specification for the materials-services elasticity is analogous).

$$\text{First stage: } \Delta\ln\left(\frac{P_i^m}{P_i^e}\right) = \rho_x \Delta\tau_i + \lambda_e + \eta_i \tag{7}$$

$$\text{Second stage: } \Delta\ln\left(\frac{PM_i}{PE_i}\right) = \beta_x \Delta\ln\left(\frac{P_i^m}{P_i^e}\right) + \lambda_e + \epsilon_i \tag{8}$$

where i denotes a plant, m denotes materials, while e denotes energy. As before, Δ stands for changes between 1989 and 1996. PM_i/PE_i are expenditures by plant i on

[27] This would be the case to the extent that there are fixed costs associated with changing the production process.

Table 5: Heterogeneity by Reform Characteristics of Industries

	Not Delicensed in 1991		Delicensed in 1991		No FDI Reform in 1991		FDI Reform in 1991	
	OLS	IV	OLS	IV	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Δln(prices)	-0.265	-2.673	-0.544	-1.014	-0.496	-2.769	-0.193	-1.357
	(0.156)	(0.850)	(0.339)	(1.235)	(0.191)	(0.888)	(0.244)	(1.097)
Elasticity	1.265	3.673	1.544	2.014	1.496	3.769	1.193	2.357
	[0.96,1.57]	[2.00,5.35]	[0.87,2.22]	[-0.44,4.47]	[1.12,1.88]	[2.00,5.54]	[0.71,1.67]	[0.19,4.52]
		First Stage		First Stage		First Stage		First Stage
Δtariffs		0.092		0.123		0.125		0.109
		(0.023)		(0.021)		(0.020)		(0.025)
F-stat		35.3		33.1		37.9		19.2
Observations	9,696	9,696	3,579	3,579	6,225	6,225	5,554	5,554
# plants	2,213	2,213	1,450	1,450	2,319	2,319	2,290	2,290

Notes: This table shows our estimation results restricting the sample to plants in 3-digit industries that were or were not exposed to delicensing reforms or FDI reforms in 1991. We obtain reform measures from Aghion et al. (2008) and describe them in more detail in Appendix B1.. The dependent variable in the OLS and IV specifications are the change in plant spending shares between 1989 and 1996. The dependent variable in the first stage is the change in material input prices between 1989 and 1996. An observation is a plant $\times$ 1-digit material input category. Standard errors are clustered at the 4-digit industry level. All regressions include plant fixed effects and 1-digit material category fixed effects. All variables are residualized before the sample is split. Regressions are weighted by the inverse of the number of inputs used by the plant. .

materials relative to expenditures on energy. $\Delta\ln\left(\frac{P_i^m}{P_i^e}\right)$ is the change in plant i's Tornqvist price index for materials relative to its price index for energy. We construct $\Delta\ln P_i^m$ analogously to $\Delta\ln P_{ik}$, aggregating across material inputs k using average plant expenditure shares. P_i^e (and P_i^s) are also a Tornqvist price index, constructed using sectoral price indices for energy inputs and service sector inputs from World KLEMS.[28]

τ_i is an import tariff measure for plant i's material input bundle. λ_e is a constant which absorbs any aggregate trends in relative expenditures or prices for materials relative to energy.[29] ρ_x is the elasticity of domestic relative input prices with respect to import tariffs. β_x is our estimate of one minus the elasticity of substitution between energy, materials and services. As a baseline, we pool together all observations and estimate a common elasticity of substitution between energy and materials and between

[28]The World KLEMS database has energy price deflators for two sectors: 'Coke, Refined Petroleum Products and Nuclear fuel' and 'Electricity, Gas and Water Supply'. It has service price deflators for four sectors: 'Transport and Storage', 'Post and Telecommunication', 'Financial Services' and 'Business Service'.

[29]In our pooled specification, there is a separate fixed effect for energy and for services. This absorbs any common trends in relative prices and spending shares of materials vs. energy and materials vs. services.

services and materials.

We use a similar specification to estimate the elasticity of substitution between intermediates and the capital-labor bundle:

$$\text{First stage: } \Delta\ln\left(\frac{P_i^x}{P_i^v}\right) = \rho_v\,\Delta\tau_i + \lambda + \eta_i \tag{9}$$

$$\text{Second stage: } \Delta\ln\left(\frac{PX_i}{PV_i}\right) = \beta_v\,\Delta\ln\left(\frac{P_i^x}{P_i^v}\right) + \lambda + \epsilon_i \tag{10}$$

An x superscript denotes intermediates and a v superscript denotes the capital-labor (value-added) bundle. $\frac{PX_i}{PV_i}$ is the expenditure share on intermediates relative to that on the value-added bundle. We construct $\Delta\ln P_i^x$ by aggregating P_i^e, P_i^m and P_i^s using Tornqvist plant expenditure shares. We use a capital deflator and an industrial worker CPI deflator from the Reserve Bank of India to construct P_i^v, aggregating the deflators using Tornqvist plant capital and labor shares. We construct the tariff instrument using the same approach as for prices, except we weight prices changes using 1989 shares rather than Tornqvist shares.

The estimation sample consists of plants which we observe in the ASI in both 1989 and 1996. It is larger than the sample we use to estimate θ because we do not need to restrict the sample to plants who use at least two categories of materials. We trim the 1% tails of spending share changes, price changes and tariff changes for our baseline results.[30] Table A.3 shows summary statistics for all of the variables used in the estimation of θ^X and ε. There are 16,884 observations and 8,616 plants in our θ^X estimation sample and 8,449 observations and plants in our ε estimation sample. The identification assumptions are the same as those laid out in Section 4.1.2.

4.2.2. Estimation Results

Table 6 presents the baseline estimates of θ^X and ε; the first two columns repeat the estimates of θ for comparison. While the estimates of θ are greater than one, both the OLS and IV estimates of θ^X and ε are less than one. The 95% confidence interval for our IV estimate of θ^X is [-0.31,1.17] and for ε is [0.02,1.21]. We therefore find evidence of substitutability between different types of materials, but complementarities between energy, materials, and services, as well as between intermediates and value-added. We show results separating energy-materials and materials-services in Table B.4, and find a somewhat higher elasticity for energy-materials. These results are robust to a number of robustness checks shown in Tables B.5 and B.6; using the same sample of plants as

[30] We find similar results when trim the left 5% tail of tariff changes. We do not trim the 5% left-tail of tariff changes in the baseline because the distribution of tariff changes is a lot less left-skewed for the estimation of θ^X and ε than for θ. This is because the more extreme tariff changes get averaged out at the plant-level.

Table 6: KLEMS Elasticity Estimates

	θ (M1-...-M8)		θ^X (E-M-S)		ε (KL-EMS)	
	OLS	IV	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)
Δln(prices)	-0.352	-2.107	0.535	0.570	0.521	0.374
	(0.154)	(0.643)	(0.183)	(0.376)	(0.154)	(0.303)
Elasticity	1.352	3.107	0.465	0.427	0.479	0.618
	[1.03, 1.65]	[1.84, 4.37]	[0.11, 0.83]	[-0.31, 1.17]	[0.18, 0.78]	[0.02,1.21]
		First Stage		First Stage		First Stage
Δtariffs		0.128		0.139		0.113
		(.016)		(0.027)		(0.024)
F-stat		63.3		25.9		23.3
Observations	13,275	13,275	16,884	16,884	8,449	8,449
# plants	5,150	5,150	8,616	8,616	8,449	8,449

Notes: This table shows our estimation results for the elasticity between material inputs θ, the elasticity between energy, materials and services θ^X, and the elasticity between intermediates and capital-labor ε. The estimation results in columns (1) and (2) are the same as those shown in Table 2. The estimation results in columns (3) and (4) are based on the estimating equations (7) and (8). The estimation results in columns (5) and (6) are based on the estimating equations (9) and (10). The dependent variable in the OLS and IV specifications are the change in industry spending shares between 1989 and 1996. The dependent variable in the first stage is the change in the appropriately constructed relative price index. In columns (1) and (2) an observation is an industry $\times$ 1-digit material input category. In columns (3) and (4) an observation is an industry $\times$ energy/service input. In columns (5) and (6) an observation is an industry. Standard errors are clustered at the 4-digit industry level. Plants are equally weighted in all specifications.

for the θ estimation, including 2-digit industry fixed effects, and restricting the sample to plants with a share of concorded inputs in 1989 greater than 95%.

4.3. Industry-Level Elasticities

The plant-level elasticities in Table 6 are important structural parameters for the macroeconomic model we present in Section 5. However, the macroeconomics and trade literatures have mostly used models where the *industry*-level elasticities of substitution are structural—constant—parameters.[31] To speak to this literature, we estimate the industry-level elasticity of substitution between 1-digit materials, between energy, materials and services, and between intermediates and value-added. This provides useful information over and above the plant-level elasticities for two reasons.

[31] Caliendo and Parro (2015) and Caliendo et al. (Forthcoming) are recent examples.

Firstly, the plant-level estimation sample is restricted to plants that are in the data in both 1989 and 1996. As shown in Table A.1, these plants tend to be larger than the typical Indian plant. The industry-level estimation on the other hand uses a larger sample that is more representative of smaller plants.

Secondly, the differences between our plant-level estimates and industry-level estimates are informative of the contribution of entrants, exiters and reallocation across plants to changes in industry input shares. As discussed in Oberfield and Raval (2021), even with constant plant-level elasticities, industry-level elasticities of substitution are not constant if plants are heterogeneous in their spending shares: changes in relative prices lead to a reallocation of inputs across plants. They show that the local industry-level elasticity of substitution between two inputs is a convex combination of the elasticity of substitution across inputs and the elasticity of demand faced by plants. It is ex-ante unclear whether industry-level estimates should be higher or lower than our plant-level estimates.

The specifications are identical to the plant-level specifications, except that the unit of production is the 4-digit industry rather than the plant. We construct industry-level expenditure shares on each intermediate input category as the sum of all expenditures by plants in that industry in a given year. We also construct industry price indices and tariff instruments in the same way as we do for plants, weighting 5-digit prices and tariffs by industry expenditure shares. As before, we drop inputs whose expenditure share in the industry is less than 0.1%, trim the 1% tails of price changes, spending share changes and tariff changes, and for the estimation of θ trim the 5% left tail of tariff changes. We also drop industries with fewer than 10 plants on average.

The estimation results are presented in Table 7. Given that there is less heterogeneity in shares at the industry-level than at the plant-level, the industry estimates are less precise than our plant estimates. However, the general picture is quite similar to that portrayed by our plant-level estimates: an elasticity greater than 1 between different categories of materials, and less than one between energy, materials and services as well as between intermediates and value-added.

5. Quantitative Model

The elasticities of substitution we estimate in this paper are crucial for answering a range of questions in macroeconomics and trade. We quantify their importance by embedding the model of plant-level production from Section 2. into a general equilibrium framework calibrated to the Indian economy. We use the model to assess the gains from India's trade liberalization and estimate the aggregate impact of two counterfactuals:

Table 7: Industry-level Elasticity Estimates

	Industry θ (M1-...-M8)		Industry θ^X (E-M-S)		Industry ε (KL-EMS)	
	OLS	IV	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)
Δln(prices)	-0.289	-3.047	0.698	-0.009	0.150	-0.392
	(0.333)	(1.563)	(0.261)	(1.538)	(0.472)	(2.105)
Elasticity	1.289	4.047	0.302	1.001	0.854	1.289
	[0.64, 1.94]	[0.97, 7.12]	[-0.21, 0.82]	[-2.02, 4.05]	[-0.07, 1.78]	[-2.75,5.53]
		First Stage		First Stage		First Stage
Δtariffs		0.123		0.122		0.094
		(.015)		(0.029)		(0.025)
F-stat		67.2		17.5		13.7
Observations	1,256	1,256	613	613	305	305
# industries	310	310	310	310	305	305

Notes: This table shows our estimation results for the industry-level elasticity between material inputs θ, the elasticity between energy, materials and services θ^X, and the elasticity between intermediates and capital-labor ε. The estimation results in columns (1) and (2) are based on the estimating equations 3 and 4. The estimation results in columns (3) and (4) are based on the estimating equations 7 and 8. The estimation results in columns (5) and (6) are based on the estimating equations 9 and 10. In all cases, the i subscript should be interpreted as representing the 4-digit industry, rather than the plant. The dependent variable in the OLS and IV specifications are the change in plant spending shares between 1989 and 1996. The dependent variable in the first stage is the change in the appropriately constructed relative price index. In columns (1) and (2) an observation is an industry $\times$ 1-digit material input category. In columns (3) and (4) an observation is an industry $\times$ energy/service input. In columns (5) and (6) an observation is an industry. Standard errors are clustered at the 4-digit industry level. Industries are equally weighted in all specifications.

closing the sectoral TFP gap to the US and changing the severity of other distortions in the economy.

Building on the canonical model of Long and Plosser (1983), we build a model of a static open economy with multiple sectors. In each sector, firms produce differentiated varieties using labor and intermediate inputs. There is balanced trade in goods, but the labor market clears domestically. On the demand side, a representative consumer has preferences over domestic and imported varieties of consumption goods produced in all sectors.

5.1. 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. In each industry j, there is an exogenous number N_j of firms. We nest the firm production function from Section 2. in the model; firm i in sector j produces a variety Q_{ji} using labor and intermediates inputs according to the following CES production function:

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

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

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

As before, ε, θ^X and θ are the respective elasticities of substitution for each input bundle.[32] We normalize the technological shifters to sum to 1 within each nest: $\pi_{ji}^e + \pi_{ji}^m + \pi_{ji}^s = 1$ and $\sum_{k=1}^{K^z} \pi_{jik}^z = 1$. 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).[33] 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 result in a misallocation of inputs both within and across sectors.

[32]We assume that the elasticity of substitution within the energy and services bundle is also equal to θ. The trade liberalization does not allow us to estimate them directly and we are not aware of any existing estimates. Our quantitative results are robust to relaxing this assumption, as reported in Table C.2 in Appendix C.

[33]Blaum et al. (2019) and Tintelnot et al. (Forthcoming) show that heterogeneity in import shares is prevalent and important for the gains from trade. However, this particular dimension of firm heterogeneity is not a focus of our paper.

Sectoral Output The varieties produced by firms in sector j are combined into a sectoral good by a perfectly competitive representative firm. This firm produces sectoral output Q_j according to the following CES aggregator:

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

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

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

Aggregate Consumption Good 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:

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

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

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

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^X, σ 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. The aggregate consumption good Y is the numéraire.

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.

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

Given that we normalized the price of the aggregate consumption good to 1, GDP in this model is simply equal to the consumption of the representative agent, C.

Equilibrium Sectoral output Q_j can either be used by firms as an intermediate input or 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:

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

We can now define a competitive equilibrium. Given a set of productivities $\{A_{ji}\}$, production technologies $\{\varepsilon, \theta^X, \theta, \eta, \{\gamma_{ji}\}, \{\pi_{ji}^z\}, \{\pi_{jik}^z\}, \{\delta_{jk}^z\}\}$, distortions $\{\tau_{ji}\}$, preferences $\{\sigma^X, \sigma, \eta_c, \{\omega^z\}, \{\omega_k^z\}\}$ 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, and 6) trade is balanced.

5.2. Calibration

We calibrate the quantitative model to match moments from plant- and sector-level data for the Indian economy, using our estimated elasticities of substitution. We refer to the calibration that uses our IV estimates of θ, θ^X and ε from Table 6 as the 'substitutes' calibration.

For the remaining elasticities in the model, we choose existing medium / long-run estimates in the literature. These are shown in Table 8. The most important of these for our counterfactual exercises are the elasticities of substitution between consumption goods. We use estimates from Hobijn and Nechio (2019), who exploit changes in European VAT rates to estimate long-run aggregate elasticities of substitution across consumption goods. We use estimates of the elasticities of substitution between domestic and imported intermediate inputs/consumption goods from Blaum et al. (2019) and Feenstra, Luck, Obstfeld and Russ (2014) respectively. The elasticity of substitution across plants 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).

We calibrate the model to match plant-level profit and cost shares from the ASI, and sector-level cost shares for the whole economy from the World Input-Output Database (WIOD). We use data from the 1996 ASI and WIOD, as this is the earliest year for which both are available. The WIOD is a database of input-output flows between 2-digit NACE sectors in 40 countries, including the U.S. and India. Domestic and imported intermediate inputs are reported separately, as are consumption of domestic and imported goods from each sector.[34] We use the Socio-Economic Accounts (SEA) to obtain labor and capital measures by sector. We assign each of the 29 sectors to an EMS category; 11 to Materials, 2 to Energy and 16 to Services.

We set the number of plants in each sector equal to 300. In order to recover the joint distribution of plant productivities, distortions and technologies, we randomly draw 300 plants from the corresponding sector in the ASI.[35] We then recover all the plant production parameters from market shares and input cost shares.[36] We infer plant-specific revenue distortions (τ_{ji}) from profit shares and estimates of sector-specific markups from De Loecker et al. (2016). Finally, we infer the consumer preference parameters ω^Z, ω^Z_k and $\delta^Z_{c,k}$ from aggregate consumption shares.

[34]The 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, Dietzenbacher, Los, Stehrer and de Vries (2015).

[35]We set the number of plants in each sector equal to 300 to reduce the computation burden when solving the model. For service and energy sectors we draw from a random sector in the ASI.

[36]We adjust the ASI input cost shares so that they aggregate to the WIOD shares.

Table 8: Elasticities in Baseline Calibration

Elasticity	Value	Description	Paper	Country
σ^X	1.0	consumption (across EMS)	Hobijn and Nechio (2019)	Europe
σ	2.6	consumption (within EMS)	Hobijn and Nechio (2019)	Europe
η	2.4	domestic & imported (intermediates)	Blaum et al. (2019)	France
η_c	2.0	domestic & imported (consumption)	Feenstra et al. (2014)	U.S.
μ	3.9	across plants	De Loecker et al. (2016)	India

6. Trade Liberalization & Counterfactuals

We use the model to show that the elasticity of substitution between material inputs we estimate matters qualitatively and quantitatively for important questions in macroeconomics and trade. To this end, we compare three different calibrations of the model – complements ($\theta = 0.1$), Cobb-Douglas ($\theta = 1$) and substitutes ($\theta = 3$) – leaving all other structural parameters constant.[37] We then discuss how the aggregate consequences of various kinds of sectoral shocks depend on the value of θ. We first analyze the gains from India's trade liberalization. We then consider the GDP impact of two sets of counterfactuals: sectoral TFP increases, as well as changes in within and across-sector misallocation.

6.1. India's Trade Liberalization: Aggregate and Distributional Consequences

In this first exercise, we use the model to quantify the gains from India's trade liberalization from the perspective of an onlooker in 1989. Because the WIOD is not available before 1995, we first construct 1989 expenditure shares for the Indian economy by reverse engineering the trade liberalization from our 1996 calibration; we increase import prices in each sector by the corresponding decline in import tariffs. We set $\theta = 3$ in this first step. We then evaluate the gains from the trade liberalization as well as the induced reallocation of resources after re-calibrating the model using alternative values of θ.

[37]We focus on the role of θ as opposed to the higher-level elasticities θ^X and ϵ since this estimate deviates most from the value typically used in the literature. We approach this from the perspective of three different researchers who make three different assumptions about the true values of θ. The inferred underlying model parameters (such as plant productivities) therefore differ across calibrations.

Model Validation

Before discussing the results, we validate the model by comparing the changes in sectoral employment during the period of the trade liberalization in model and data. To this end, we aggregate sectoral employment using the plant-level data from the ASI, concorded to the nine manufacturing sectors in the WIOD.[38] Defining the pre- and post-reform years as 1989 and 1996 like in the estimation, we compute changes in sectoral employment relative to the growth of employment in manufacturing overall. We then compare these changes in employment to the changes predicted by the calibrated model when feeding in observed changes in import tariffs.

The results suggest that the calibrated model captures changes in sectoral employment well. Importantly, the high substitutability of intermediate inputs significantly improves the fit of the model. Had we imposed that intermediates were complements also over the medium run ($\theta = 0.1$), the correlation of sectoral employment changes in model and data would be 0.13. The correlation increases to 0.31 with unitary elasticities. When using our estimated elasticities of substitution of 3, model-implied sectoral labor changes have a correlation of 0.66 with the data. Given that this is a relatively long period and one in which other sectoral policies were implemented, we view this as a success for the model and an indication of the importance of input substitutability over the medium run.

Results

In an economy with non-unitary elasticities and firm heterogeneity in technology, tariff reductions induce reallocation both across sectors and across firms. The first source of reallocation is driven by our estimated elasticities–all firms substitute towards cheaper intermediate inputs. This reallocation quantitatively dominates the reallocation across firms, which is driven by technology differences. 97% of workers who change jobs move to a different sector and only 3% to a different firm in the same sector.[39] We therefore focus on the labor reallocation across sectors induced by the trade liberalization.

As sectors and plants differentially grow and shrink, workers move. The exact pattern of reallocation depends crucially on the elasticity of substitution between materials. In the aggregate, we find that, when θ is higher, the extent of reallocation is substantially higher. Quantitatively, in the baseline calibration, 1.0% of the Indian workforce gets displaced out of the sector they work in. In a world of complementary inputs (Cobb-Douglas) that number is only about two thirds, or 0.6% (0.7%) of the workforce. This is simply a consequence of the fact that the more substitutable intermediate inputs are,

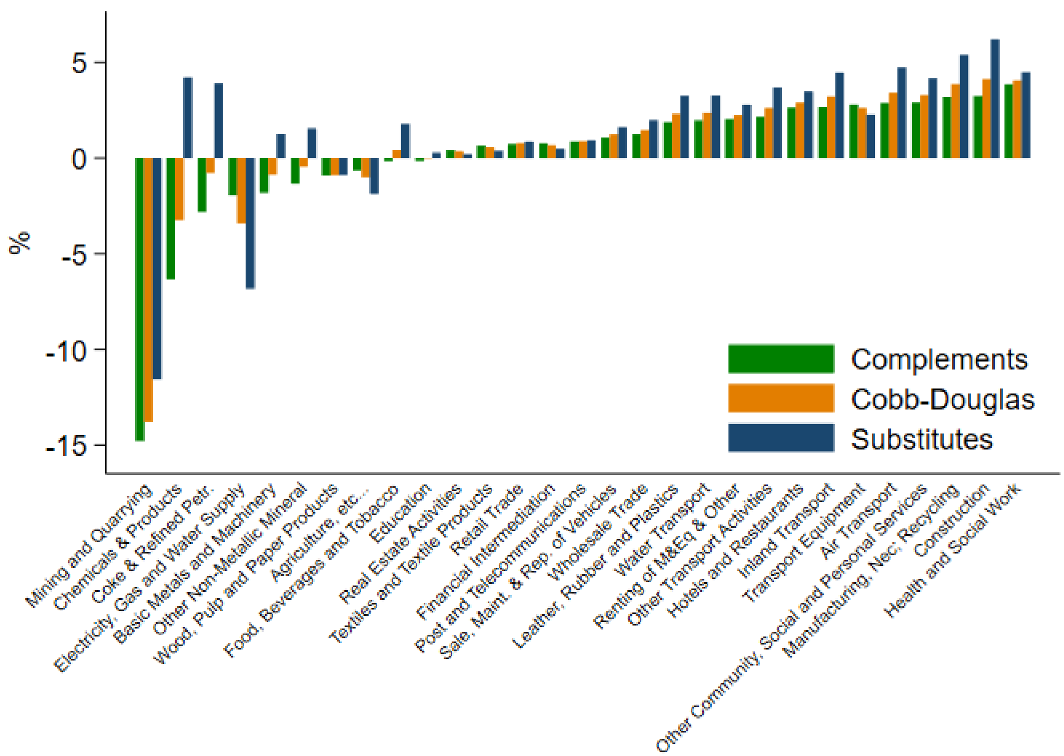
[38]We focus on manufacturing because this allows us to use the ASI data and because we estimated the elasticity across inputs from manufacturing sectors.

[39]With a high elasticity of substitution between intermediate inputs, there is less heterogeneity in the effect on firm's input prices by technology and hence less scope for firm's market shares to adjust.

the more firms in each sector substitute towards now cheaper inputs, causing the more productive sectors to grow.[40]

Figure 4 plots the model-implied changes in employment in the 29 sectors for the three calibrations of the model: intermediates are complements, Cobb-Douglas, and substitutes as we estimate. Interestingly, the difference between an economy where intermediate inputs are complements and one with unitary elasticities is modest. In particular, the set of sectors that see their workforce grow as a result of the trade liberalization is unchanged. In contrast, when allowing intermediate inputs to be as substitutable as we estimate, changes in sectoral employment are qualitatively and quantitatively different.

Figure 4: Changes in Sectoral Employment Induced by the Trade Liberalization



Notes: This figure shows the model % changes in labor in each sector following the observed reduction in import tariffs. Each column corresponds to a different calibration of the model. The first column is the complements calibration, where $\theta = 0.1$. The second column is the Cobb-Douglas calibration, where $\theta = 1$. The third column is the substitutes calibration, where $\theta = 3$.

[40] The reason there is less reallocation with complementary intermediate inputs than with Cobb-Douglas is that we keep the substitutability on the consumption side when re-calibrating θ. As a result, even though complementary inputs on their own would lead to more re-allocation, the combination with substitutes on the consumption side then on net moves the economy closer to unitary elasticities where reallocation is lowest.

For example, there are several sectors that would see employment shrink with lower elasticities of substitution, but grow when intermediate inputs are substitutes. Two such prominent examples are "Chemicals & Products" and "Coke & Refined Petroleum". Both sectors saw a decline in their overall input price index following the trade liberalization. When intermediate inputs are substitutes, there is reallocation towards these now cheaper inputs and the sectors grow. The opposite happens in the case of complementary intermediates, when resources are reallocated away from the now relatively more productive sectors. The magnitudes are large: while the number of workers employed in chemicals production would shrink by over 6% if material inputs were complements, the sector grows by around 4% in our calibration.

In a more substitutable economy, there is not only more reallocation as a result of any set of sectoral shocks, but the heightened ability to reallocate towards now cheaper sectors amplifies the aggregate effects of the initial shock. In the case of the trade liberalization, the resulting changes in aggregate output are shown in Table 9. The increase in aggregate consumption or GDP is 2.14% when intermediate inputs are complements, 2.23% when they are neither complements nor substitutes, and 2.44% when they are substitutes. The gains with our estimated elasticities of substitution are therefore 9% larger than under the Cobb-Douglas calibration and 14% larger than under the complements calibration.[41]

Table 9: Aggregate Gains from India's Trade Liberalization

	Complements	Cobb-Douglas	Substitutes
Trade Liberalization	2.14%	2.23%	2.44%

Notes: This table shows the aggregate increase in GDP from India's trade liberalization through the model. Each column corresponds to a different calibration of the model. The first column is the complements calibration, where $\theta = 0.1$. The first column is the Cobb-Douglas calibration, where $\theta = 1$. The third column is the substitutes calibration, where $\theta = 3$.

6.2. Closing Sectoral TFP gaps

As a second exercise, we use the model to predict the aggregate gains of an increase in sectoral TFP in one sector of the economy. For concreteness, we focus on TFP increases that would close the gap between India and the U.S. in that sector. We measure India-U.S. TFP gaps using the WIOD and SEA, combined with PPP prices from Inklaar and Timmer (2013) (see Figure C.2 in Appendix C). Sectoral TFP gaps between India and the

[41] 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)).

U.S. are large and heterogeneous. On average, Indian sectoral TFP needs to be almost doubled to close the gap with the U.S. We implement the counterfactual in the model by scaling up the productivity of each plant in the sector by the TFP gap.[42]

Before discussing the results of this specific counterfactual, we again validate the model and our estimated elasticity by comparing model-predicted changes in the input-output structure to the data, this time by feeding in observed sectoral TFP changes from 1996 to 2005. Similar to the validation of labor reallocation following the trade liberalization, we find that with our estimate of $\theta = 3$, the quantitative model fits the observed distribution of sectoral changes (in terms of sales to both consumers and to downstream sectors) reasonably well. With unitary elasticities or complementarities between intermediate inputs, the correlation between model and data is much lower, and in the case of sales to downstream sectors even negative. Detailed description and results are in Appendix C1..

Figure 5 summarizes the results of the counterfactual closing of the TFP gap to the US under each of the three calibrations. Averaging across all sectors, the aggregate gains are 29% larger when using our estimated elasticities of substitution compared to the Cobb-Douglas calibration, and 42% larger than in the complements calibration. There is also considerable heterogeneity across sectors in how much intermediate input elasticities matter. For example, the gains from closing TFP gaps in sectors such as 'Wood, Pulp and Paper Products' are more than twice as large in the substitutes calibration as in the complements calibration, but almost identical in 'Food, Beverages and Tobacco'.

We show in Appendix C2. how the amplification relative to Cobb-Douglas systematically depends on two factors. First, the larger is the TFP gap, the bigger are the second-order effects and hence the more non-unitary elasticities matter in the aggregate. Second, the more a given sector is used as an intermediate input rather than for final consumption, the more there is potential for amplification through input substitutability.

6.3. Misallocation

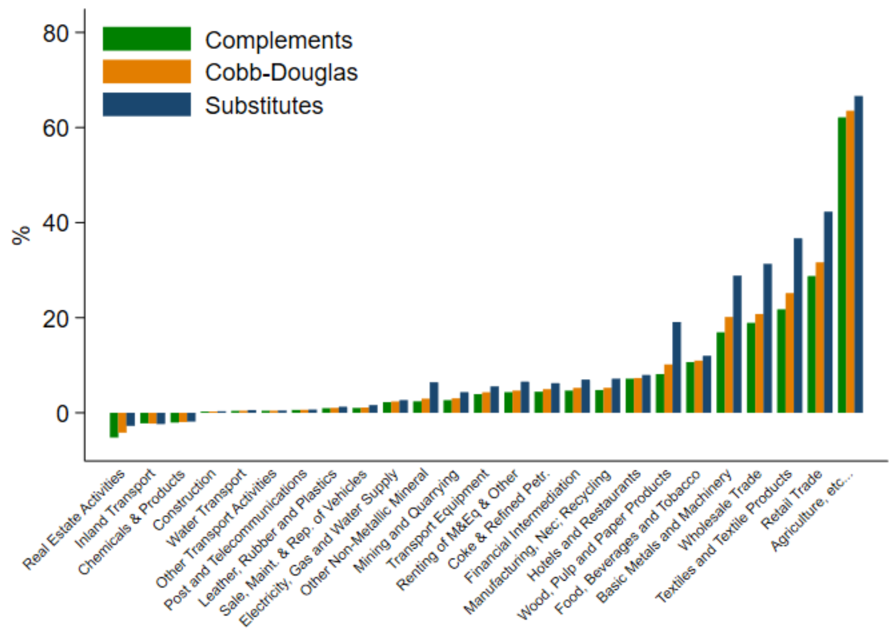
Revenue distortions

As a third exercise, we evaluate the aggregate productivity gains from reducing dispersion in revenue distortions: i.e. improving allocative efficiency. We consider three counterfactual exercises: 1) setting all distortions to zero, 2) removing within industry dispersion in revenue distortions only, and 3) removing across industry dispersion in distortions only. The results are shown in the first three rows of Table 10.

We find that the gains from removing all distortions are 15% of GDP in the comple-

[42]A certain share of India-U.S. sectoral TFP gaps may be accounted for by resource misallocation. However, measuring relative resource misallocation in the U.S. and India is made difficult by measurement error (Bils, Klenow and Ruane (2021)) and imputation in the U.S. Census (Rotemberg and White (2019)).

Figure 5: Aggregate Gains from Closing TFP Gaps



Notes: This figure shows the model % GDP gains from closing the India-U.S. sectoral TFP gap of the sector shown in Figure C.2. Each column corresponds to a different calibration of the model. The first column is the complements calibration, where $\theta = 0.1$. The second column is the Cobb-Douglas calibration, where $\theta = 1$. The third column is the substitutes calibration, where $\theta = 3$.

ments calibration but 20% in the substitutes calibration, 31% larger. When we remove only within-sector dispersion in distortions however, we find that the counterfactual gains are more similar across calibrations, ranging from 11.5% to 12.5%. Intermediate input elasticities are much more important for the gains from removing across-industry dispersion in distortions. These are only 0.1% in the complements calibration but increase by a factor of 6 to 0.6% in the substitutes calibration.

The difference in the importance of intermediate input elasticities stems from the fact that removing within-sector dispersion in distortions acts like a small increase in sectoral TFP. As discussed in the previous sub-section, this implies a small role for elasticities in the model. However, reducing dispersion in across-sector distortions reduces across-sector resource misallocation. This misallocation is considerably worse when inputs are more substitutable, because quantities of inputs move more in response to sectoral price distortions. This counterfactual therefore suggests that there is a larger role of across-sector misallocation than one would conclude based on a standard Cobb-Douglas calibration.

Table 10: Allocative Efficiency Counterfactuals

	Complements	Cobb-Douglas	Substitutes
Across and Within Industry ($\tau_{ij} = 0$)	15.03%	15.70%	17.57%
Within Industry ($\tau_{ij} = \tau_j$)	11.49%	11.67%	12.10%
Across Industry ($\tau_j = 0$)	0.12%	0.23%	0.62%
Across Inputs ($\tau_{ji}^k \neq 0$)	-2.33%	-5.71%	-19.1%

Notes: The results in the table contrast the % gains predicted by our model for various counterfactuals described in the leftmost column.

Misallocation of Inputs

As a final exercise, we evaluate the losses caused by distortions to input prices. In the quantitative model, we assumed that all heterogeneity in plant spending shares is a result of different technologies used. Suppose instead that all plants in industry j had the same production technologies π_j^z and the dispersion in spending shares observed in the data was due to input-specific distortions τ_{ij}^k. These could represent for example heterogeneity in input prices due to contracting frictions (Boehm, 2022), transportation cost, different markups charged by intermediaries, or literal taxes and subsidies. If we interpret heterogeneity in spending shares across firms within industries as resulting from distortions, the implied distortions have a log standard deviation of 1.46.

The counterfactual we consider is adding input distortions to the quantitative model described in Section 5. The distortions are drawn from a lognormal distribution with mean zero and variance equal to 1/3 of the observed dispersion in the data. We choose 1/3 as the benchmark number so as to not overstate the degree of revenue distortions, since some of the observed heterogeneity is likely due to technology or measurement error.[43]

The last row of Table 10 lists the losses from such an increase in the dispersion of input distortions. These are average numbers from running the counterfactuals with 20 different draws of input distortions. We find that the aggregate losses would be around 6% of GDP if the elasticity of substitution between intermediates inputs was equal to 1. They increase to 19% of output with our estimated elasticities, more than three times

[43] Alternatively, we could have interpreted all heterogeneity in spending shares as due to input distortions and run a counterfactual that removes them. This is unappealing however, since the size of implied distortions then depend on the intermediate input elasticities and we can no longer compare the gains from reducing misallocation across different values of the elasticity of substitution.

larger. If intermediate inputs were complements on the other hand, the losses would be more than 9 times lower than with our preferred estimates. These results suggest that there are potentially large losses from input-specific distortions, especially if these distortions are heterogeneous across inputs. Since we estimate intermediate inputs and value added to be complements in production, uniform distortionary taxes on inputs would imply much smaller efficiency losses.

6.4. An Alternative Mechanism: Multi-Product Plants

As mentioned in Section 4., our empirical findings could be generated by a slightly different mechanism – plants switching between products. We cannot 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 their factor intensity. 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.

We therefore evaluate how much our counterfactuals would be affected if indeed product substitution was driving our empirical results. In Appendix C4. we develop such an alternative model and choose its structural elasticities to match the same – now reduced-form – relationship between relative prices and relative expenditure shares. 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 C.6). 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 provides a quantitatively reasonable approximation to alternative models with multi-product plants.

7. Conclusion

In this paper, we provide the first estimates of long-run elasticities of substitution between intermediate inputs at the plant-level. The empirical setting – the manufacturing sector during India's trade liberalization – provides us with the unique combination of detailed data and quasi-exogenous variation necessary for estimation. We find an elasticity of substitution between broad categories of materials around 3 – a significant departure from the Cobb-Douglas benchmark. Our estimate is also much higher than the value typically estimated at business cycle frequencies – close to zero. At higher levels of aggregation, between materials, services, and energy as well as between value-added and intermediates, inputs are complements even at a longer time horizon.

The value of the elasticity of substitution between intermediate inputs is crucial for a wide range of questions in macroeconomics and trade, such as the gains from trade and associated distributional effects, development accounting, and assessing the distortionary role of taxes or other wedges. We carefully quantify the importance of our estimated elasticities for each of these by building a multi-sector general equilibrium model with a rich input-output structure, calibrated to the Indian economy.

When intermediate inputs are highly substitutable, there are larger gains from trade in intermediate inputs, but these come with larger distributional consequences: twice as many workers move across sectors as in a benchmark economy with unitary elasticities. Further, TFP improvements in individual sectors have the potential to significantly lift aggregate output – the gains from closing the India-U.S. TFP gap in a single sector are on average 29% larger. Last, we show that our estimated elasticities have important consequences for assessing the role of losses due to misallocation. For example, increasing input distortions by the same order of magnitude as we infer from the Indian data leads to losses that are more than three times larger than in a Cobb-Douglas economy.

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Appendix
For Online Publication

A Datasets

A1. Annual Survey of Industries

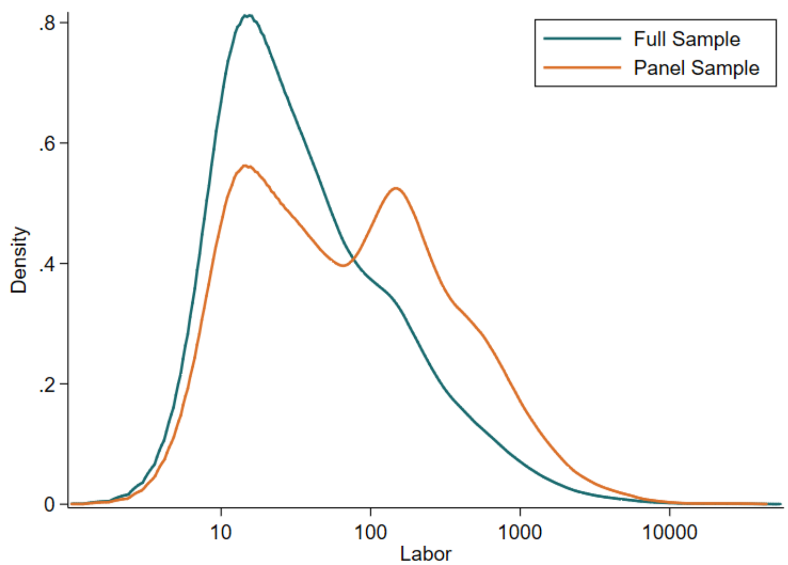
The ASI is a nationally representative yearly survey of registered Indian manufacturing plants. The surveys cover accounting years (e.g. 1989-1990), but we refer to each survey by the earlier of the two years covered. The coverage of the survey is all plants with more than 10 workers using power and all plants with more than 20 workers not using power. ASI sampled plants fall into two 'schemes': *Census* and *Sample*. *Census* plants, which include all plants with more than 100 workers are surveyed every year.[44] 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. We use panel identifiers from a previous release of the ASI (see Alcott et al. (2016) and Bils et al. (2021)).

Only the 'detailed' releases of the ASI contain information on the values and quantities reported by plants for each of their intermediate inputs. These are available in 1989, 1993, 1994 and from 1996 on. We don't use the 1997 and 1998 surveys because of poor reporting quality.[45] We therefore use the 1996 ASI as our post-trade liberalization year.

[44] 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.

[45] From 1997 on plants only needed to report their top 5 most used inputs. In addition, the share of inputs classified as 'Other' increased dramatically.

Figure A.1: Labor Distribution in Full Sample and Estimation Sample



Notes: The figure shows the kernel density plots (with a bandwidth of 0.1) of labor in the 'Full Sample' of ASI plants and in the 'Panel Sample'. We pool the years 1989 and 1996. Other summary statistics comparing the 'Full Sample' and 'Panel Sample' are shown in Table A.1.

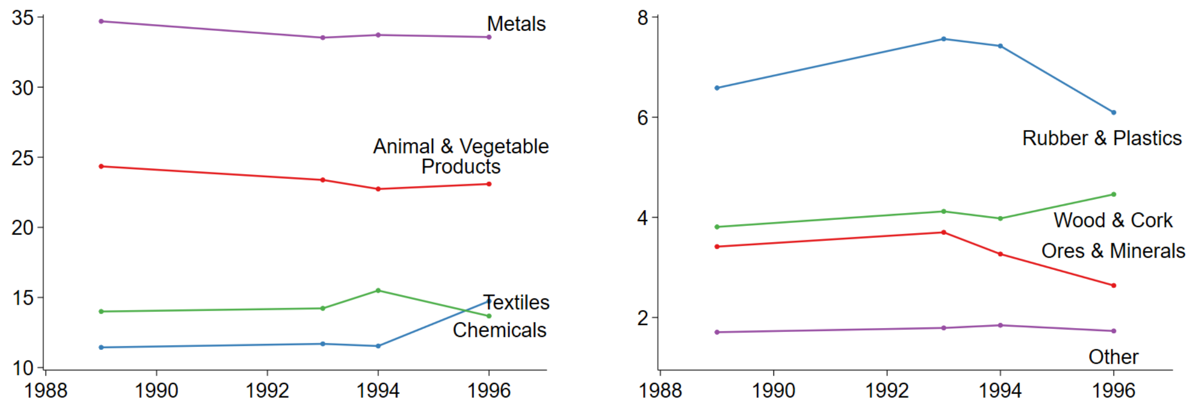
Table A.1: ASI Sample Statistics

	Full Sample	Panel Plants	θ Estimation Sample
1989 ASI Survey			
# Plants	34,197	9,380	5,150
Median Age	11	12	13
Median/Mean Labor	29/145	38 / 184	53 / 251
Mean Materials share of intermediates	78.4%	80.0%	82.9%
Mean Intermediates share of output	81.6%	78.1	78.2%
Share of Aggregate Output	100%	33.1%	21.9%
Share of Aggregate Materials	100%	32.7%	20.0%
1996 ASI Survey			
# Plants	40,959	9,380	5,150
Median Age	12	19	20
Median/Mean Labor	29/133	33 / 173	48 / 237
Mean Materials share of intermediates	76.7%	76.6%	79.6%
Mean Intermediates share of output	75.6%	75.6%	76.4%
Share of Aggregate Output	100%	25.4%	17.1%
Share of Aggregate Materials	100%	25.3%	16.0%

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 1996. 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 1996. The changes in median age for panel plants between 1989 and 1996 may not exactly consistent due to misreporting.

A2. Intermediate Input Shares

Figure A.2: Aggregate 1-digit ASICC Spending Shares (%)



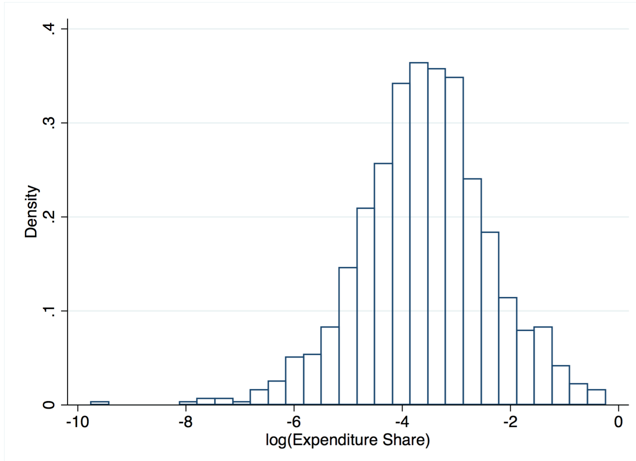
Notes: This figure plots the aggregate expenditure shares of the 8 1-digit ASICC categories of material inputs from the Annual Survey of Industries in 1989, 1993, 1994 and 1996.

Table A.2: ASICC Main Categories and Most Commonly Used Inputs

1-digit and 3-digit ASICC	5-digit ASICC
1. Animal and Vegetable Products	
123. Unmilled cereals and pulses	12301. Paddy, excluding paddy seed
131. Sugar, Mollasses, Khandsari and Gur	13103. Sugarcane
2. Ores and Minerals	
211. Salts, sulphur, lime, stone, granites and marble	21113. Sulphur
214. Clay, Kaolin, Earth, Graphite, Sand and Quartz	21438. Sand
3. Chemicals	
317. Inorganic gases	31301. Oxygen
313. Sodium and Potassium Compounds	31301. Caustic Soda
4. Rubber, Plastics and Leather	
421. Bags/boxes/panels/containers of plastic/PVC	42111. Polythene bags
41. Rubber	41135. V Belts
5. Wood, Cork and Paper	
571. Packing materials made of paper	57105. Cardboard boxes
512. Wooden furniture, boxes and other articles	51239. Wooden boxes
6. Textiles	
654. Man-made articles of natural fibre	65403. Non-laminated gunny bags
659. Other jute and natural fibre goods	65906. Jute twine
7. Metals	
750. Non-electrical machine tools	75005. Ball/roller bearings
74. Miscellaneous manufacture of base metals	74171. Nuts, bolts, etc. (not iron/copper)
9. Other Manufactured Articles	
941. Glass and glassware	94167. Glass tubes
941. Glass and glassware	94131. Glass bottles

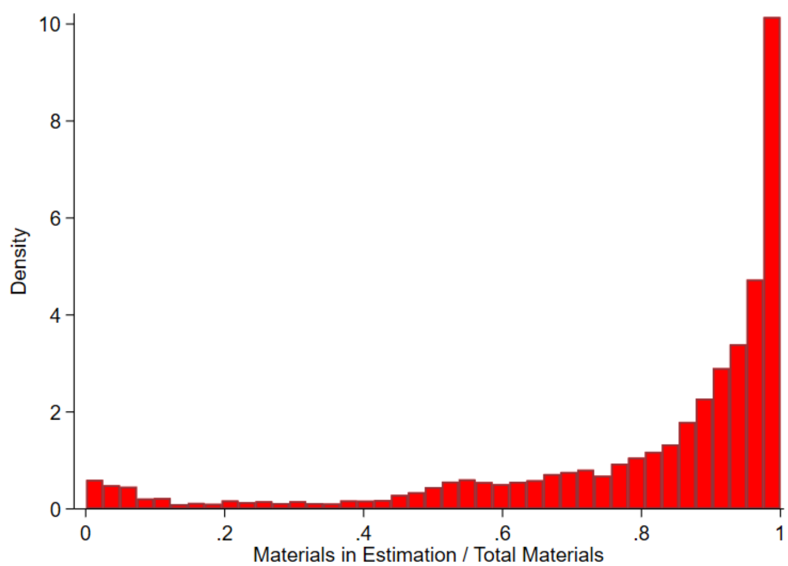
Notes: This table lists the 8 1-digit material ASICC categories we consider. Category '8. Transport Equipment' is ommitted because it is almost never reported in the materials section of the ASI surveys. The 5-digit ASICC inputs listed are the two most frequently used inputs in the 1989 ASI survey.

Figure A.3: Histogram of Log(Spending Shares) on Material Input 'Textiles' in Industry 'Manufacture of Vegetable Oils and Fats Through 'Ghanis"



Notes: This 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

Figure A.4: Share of Plant Materials Accounted for in Estimation



Notes: This figure plots the distribution of the share of material inputs accounted for in the estimation of θ. This is not 1 because inputs may not appear in both year, or some inputs may be missing data on either tariffs or prices. We report the average of 1989 and 1996 shares.

Table A.3: Summary Statistics

Variable	Mean	Std. Dev.	P1	P10	P90	P99
			θ^X Estimation			
Δln(relative spending share)	-0.23	0.83	-2.54	-1.25	0.76	1.80
Δln(relative price)	-0.13	0.12	-0.45	-0.27	0.02	0.14
Δtariff	-0.55	0.28	-1.53	-0.90	-0.26	-0.10
			ε Estimation			
Δln(relative spending share)	-0.12	0.65	-1.90	-0.94	0.68	1.43
Δln(relative price)	-0.07	0.09	-0.35	-0.18	0.04	0.11
Δtariff	-0.55	0.28	-1.53	-0.90	-0.26	-0.10

Notes: The table contains summary statistics for main variables used in the estimation of θ^X and ε.

A3. Input Classifications and Concordances

Table A.4: ASI 1-digit Categories of Energy, Materials and Services

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		

Notes: This table show the 1-digit classification of energy inputs, material inputs and service inputs in the ASI. The material input category 'Railways/Airways/Ships & Transport Equipment' is dropped from the analysis because it is almost never used as an intermediate input by manufacturing plants.

Table A.5: 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

Notes: This table show examples of our concordance of the 1989 ASI Item Codes to the ASICC classification used in 1996. Some item codes are concorded to a single 5-digit ASICC code while others are concorded to multiple 5-digit codes. Some item codes, such as Dyes, are so broad that we concord them directly to a 3-digit ASICC code. The concordance was done manually. The Item Code classification used between 1989 and 1994 had 4-digit industry-specific codes. In total, we concord 19,807 industry-item codes with 6,645 unique descriptions to 2,784 5-digit ASICC categories and 224 3-digit ASICC categories.

Table A.6: 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-Flexbile)	–	–
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

Notes: This table show examples of our concordance of the ASICC classification to the Wholesale Price Index commodity classification (base year 1981). In total we concord 383 WPI commodity codes to 617 5-digit ASICC codes.

B Empirical Analysis

Table B.1: 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%

Notes: The reported statistics are constructed from the 1989 and 1996 ASI surveys. The 'Inputs Dropped' row reports the average (value) share of inputs that were used by plants in 1989 but not in 1996. The 'Inputs Added' row reports the average (value) share of inputs that were used by plants in 1996 but not in 1989.

Table B.2: Trade Liberalization and Pre-Reform Industry Characteristics

	Panel A: Industry Characteristics in 1988					
	ln(output)	ln(labor)	ln(capital)	ln(materials)	capital share	intermediate share
1989-1996 changes in:						
Input Tariffs	0.550	0.659	0.464	0.503	0.046	0.025
	(0.373)	(0.352)	(0.388)	(0.393)	(0.031)	(0.019)
	302	302	302	302	302	302
Output Tariffs	-0.231	0.071	-0.298	-0.242	- 0.033	-0.010
	(0.267)	(0.250)	(0.291)	(0.273)	(0.023)	(0.015)
	271	271	271	271	271	271

	Panel B: Industry Pre-Trends from 1985-1988					
	Δln(output prices)	Δln(real output)	Δln(labor)	Δln(capital)	Δln(real materials)	Δln(TFP)
1989-1996 changes in:						
Input Tariffs	0.028	-0.278	0.046	0.005	-0.231	0.013
	(0.034)	(0.287)	(0.217)	(0.281)	(0.231)	(0.051)
	270	270	270	270	270	270
Output Tariffs	-0.002	-0.029	0.073	-0.046	- 0.074	-0.012
	(0.021)	(0.159)	(0.148)	(0.192)	(0.163)	(0.041)
	271	271	271	271	271	271

Notes: Each cell in this table is the result of a separate regression of the dependent variable in the corresponding column against changes in input tariffs or output tariffs between 1989 and 1996 (a 50 p.p. reduction corresponds to a value of -0.5). The unit of observation in each regression is a 4-digit NIC industry. Regressions are unweighted and standard errors are robust. The number of observations in each regression is reported in the table. Input (output) tariffs at the industry level are constructed as the weighted average of 5-digit ASICC tariffs, where the weights are given by the industry's 5-digit ASICC expenditure (output) shares as reported in the 1996 ASI. Industry output prices and material input prices are constructed in the same way using the WPI at the 5-digit ASICC level. We prefer using the 1996 ASI to the 1989 ASI because it does not rely on the accuracy of our ASICC concordance. In Panel A, the capital share is constructed as R$\times$ capital / (labor costs + R$\times$ capital), assuming a rental rate for capital R = 20%. The intermediate share is constructed as intermediates / (intermediates + labor costs + R$\times$ capital). Real output is deflated using our industry output price index, and real materials are deflated using the industry materials price index. TFP growth is constructed as real output growth - $\alpha_s\gamma_s\times$ real capital growth - $(1-\alpha_s)\gamma_s\times$ labor growth - $(1-\gamma_s)\times$ intermediates growth, where α_s is the average industry capital share between 1985-1988, and $(1-\gamma_s)$ is the average industry intermediate share between 1985-1988. All results are quantitatively similat when we use 1991-1997 changes in tariffs, industry characteristics in 1990 and 1985-1990 industry pre-trends.

Table B.3: Additional Robustness of θ Estimates

	Not Trimming 5% Tariffs		2% Trimming		Value Share $> 1\%$		Concorded Share$> 95\%$		No 1-digit Fixed effects		Aggregate 3-digit Shares	
	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Δln(prices)	-0.337	-3.717	-0.349	-1.937	-0.368	-2.199	-0.330	-2.192	-0.267	-1.412	-0.303	-1.710
	(0.157)	(0.941)	(0.162)	(0.669)	(0.195)	(0.869)	(0.157)	(0.647)	(0.150)	(0.485)	(0.163)	(0.523)
		First Stage		First Stage		First Stage		First Stage		First Stage		First Stage
Δtariffs		0.085		0.116		0.137		0.132		0.156		0.161
		(.011)		(.010)		(.020)		(.017)		(.016)		(0.014)
Observations	14,295	14,295	12,177	12,177	10,645	10,645	12,180	12,180	13,275	13,275	13,275	13,275
# plants	5,412	5,412	4,827	4,827	5,150	5,150	4,724	4,724	5,150	5,150	5,150	5,150

Notes: This table shows our estimation results under various robustness specifications. The dependent variable in the OLS and IV specifications are the change in plant spending shares between 1989 and 1996. The dependent variable in the first stage is the change in material input prices between 1989 and 1996. An observation is a plant $\times$ 1-digit material input category. Standard errors are clustered at the 4-digit industry level. All regressions include plant fixed effects, and all except columns (9) and (10) include 1-digit material category fixed effects. Regressions are weighted by the inverse of the number of inputs used by the plant. The 'No Trimming 5% Tariffs' specification does not trim the 5% left tail of tariff changes, as we do for the baseline specification. The '2% Trimming' specification trims the 2% tails of prices, tariffs and value shares rather than 1% shares. The 'Value Share $> 1\%$' specification restricts the sample to inputs that account for at least 1% of average expenditures instead of 0.1%. The 'Concorded Share$> 95\%$' specification restricts the sample to plants for which at least 95% of material expenditures in 1989 were concorded to the ASICC classification. The 'No 1-digit Fixed effects' specification doesn't have 1-digit ASICC fixed effects. The 'Aggregate 3-digit Shares' constructs the price and tariff variables using aggregate 3-digit spending shares, rather than plant 3-digit spending shares.

Table B.4: Heterogeneity in θ^X estimates for Energy and Services

	Materials-Energy		Materials-Services	
	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)
Δln(prices)	0.491	-0.184	0.310	0.509
	(0.145)	(0.615)	(0.116)	(0.603)
Elasticity	0.509	1.180	0.690	0.483
	[0.22,0.79]	[-0.29,2.39]	[0.46,0.92]	[-0.70,1.67]
		First Stage		First Stage
Δtariffs		0.084		0.091
		(0.016)		(0.018)
F-stat		26.8		25.8
Observations	8,407	8,407	8,477	8,477
# plants	8,407	8,407	8,477	8,477

Notes: In this table we report our estimation results separately between materials and energy, and between materials and services. The estimation results are based on the estimating equations 7 and 8.The dependent variable in the OLS and IV specifications are the change in plant spending shares between 1989 and 1996. The dependent variable in the first stage is the change in the appropriately constructed relative price index. An observation is a plant $\times$ energy/service input. Standard errors are clustered at the 4-digit industry level. Plants are equally weighted in all specifications.

Table B.5: Robustness of θ^X Estimates

	θ Sample		2-digit Industry FEs		Concorded Share $> 95\%$	
	OLS	IV	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)
Δln(prices)	0.749	0.820	0.403	0.179	0.388	0.222
	(0.210)	(0.480)	(0.112)	(0.536)	(0.115)	(0.565)
Elasticity	0.251	0.180	0.597	0.821	0.612	0.778
	[-0.16,0.76]	[-0.76,1.12]	[0.38,0.82]	[-0.18,1.93]	[0.39,0.84]	[-0.26,1.96]
		First Stage		First Stage		First Stage
Δtariffs		0.116		0.0880		0.0894
		(0.024)		(0.017)		(0.017)
F-stat		23.9		26.5		25.4
Observations	10,002	10,002	16,884	16,884	15,588	15,588
# plants	5,054	5,054	8,616	8,616	7,941	7,941

Notes: The estimation results are based on the estimating equations 7 and 8.The dependent variable in the OLS and IV specifications are the change in plant spending shares between 1989 and 1996. The dependent variable in the first stage is the change in the appropriately constructed relative price index. An observation is a plant $\times$ energy/service input. Standard errors are clustered at the 4-digit industry level. Plants are equally weighted in all specifications. The 'θ Sample' columns use the same sample of plants as in the estimation of θ. The '2-digit Industry FEs' specification includes 2-digit industry FEs. The 'Concorded Share$> 95\%$' specification restricts the sample to plants for which at least 95% of material expenditures in 1989 were concorded to the ASICC classification.

Table B.6: Robustness of ε Estimates

	θ Sample		2-digit Industry FEs		Concorded Share $> 95\%$	
	OLS	IV	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)
Δln(prices)	0.633	0.328	0.338	-0.100	0.486	0.423
	(0.281)	(0.480)	(0.110	(0.600)	(0.163)	(0.295)
Elasticity	0.367	0.672	0.662	1.084	0.514	0.577
	[-0.18,0.92]	[-0.27,1.62]	[0.45,0.88]	[-0.08,2.28]	[0.19,0.83]	[0.00,1.16]
		First Stage		First Stage		First Stage
Δtariffs		0.0966		0.0708		0.118
		(0.0162)		(0.0142)		(0.0251)
F-stat		35.5		24.7		22.1
Observations	4,962	4,962	8,449	8,449	7,767	7,767
# plants	4,962	4,962	8,449	8,449	7,767	7,767

Notes: The estimation results are based on the estimating equations 9 and 10. The dependent variable in the OLS and IV specifications are the change in plant spending shares between 1989 and 1996. The dependent variable in the first stage is the change in the appropriately constructed relative price index. An observation is a plant. Standard errors are clustered at the 4-digit industry level. Plants are equally weighted in all specifications. The 'θ Sample' columns use the same sample of plants as in the estimation of θ. The 'Non-importers' specification restricts the sample to plants that don't import in either 1989 or 1996. The 'Concorded Share$> 95\%$' specification restricts the sample to plants for which at least 95% of material expenditures in 1989 were concorded to the ASICC classification.

B1. Correlation between Tariff Changes and Other Reforms

The trade liberalization was not the only major nationwide reform that occurred during the 1980s and 1990s in India. Another set of important reforms was the process of removing the strict industrial licensing requirements which were first introduced by the Industries Development and Regulation Act of 1951. This licensing meant that registered manufacturing plants were required to obtain government approval whenever they wanted to open a new factory, significantly expand production or create a new product, or change location. These licensing requirements were removed in 1985 for roughly half of India's 3-digit manufacturing industries, with most of the remaining industries delicensed in 1991 as part of the major wave of reforms.[46] Similarly, while there had historically been strict restrictions on FDI, these were also relaxed in a number of industries in 1991.

A concern with our identification strategy is that the tariff declines during India's trade liberalization were correlated with either FDI reforms or industrial decilensing reforms. If these reforms increased manufacturing plants' use of inputs through any mechanism other than price (e.g. quality changes, new product lines) then they would enter into the residual of Equation 4 and bias our IV estimate β_m. In particular, this could introduce an upward bias in our estimate of θ, θ^X and ε for the same reasons that we discuss in Section 4.1.4. and Equation 11.

To deal with this concern, we examine how industry-level measures of FDI reform and industrial delicensing correlate with tariff changes on goods produced in those industries. We obtain data on all three of these at the 3-digit industry level (roughly 100 industries) from the replication package of Aghion et al. (2008). The measure of industrial delicensing is a binary 0-1 variable which equals 1 if the industry was delicensed in 1991 and 0 otherwise. The authors look at statements on industrial policy, press notes, and notifications issued by the federal government to determine when each three-digit industry was delicensed. We construct a similar binary 0-1 variable for whether a 3-digit industry underwent FDI reform in 1991.[47] 51 out of 112 industries were delicensed in 1991, and 63 industries underwent FDI reform.

The mean 1991-1997 tariff change for industries delicensed in 1991 was -82.0%, compared to -81.7% for industries which weren't delicensed. The mean 1991-1997 tariff change for industries with FDI reform in 1991 was -81.3%, compared to -82.6% for industries without FDI reform. Neither of the differences are statistically significant.[48] To

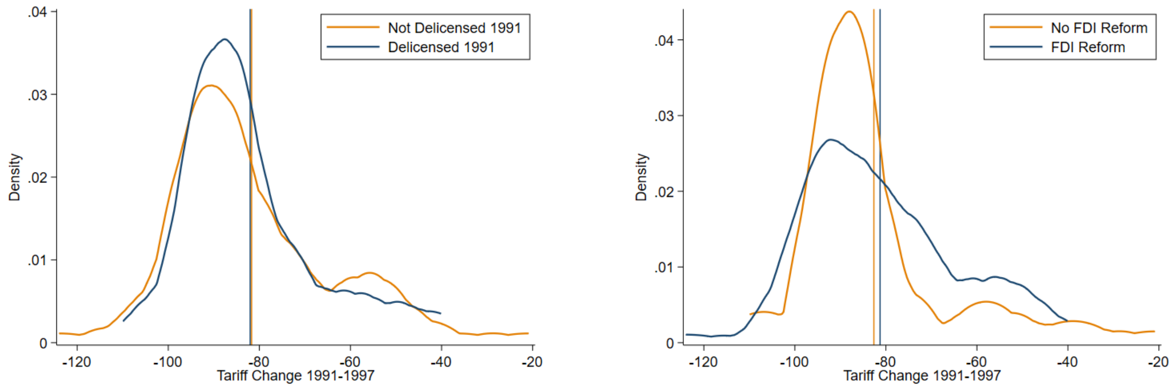
[46] One tenth of 3-digit industries were not yet delicensed by 1997.

[47] Aghion et al. (2008) construct their FDI measure as the share of six-digit products within a three-digit industry which were opened to automatic approval of FDI. We define an industry as undergoing FDI reform if any 6-digit product was opened up to automatic approval of FDI.

[48] The corresponding numbers for 1989-1996 tariff are similar and not statistically different from each other. The 1989-1996 tariff change for industries delicensed in 1991 was -80.1%, compared to -77.6% for industries which weren't delicensed. The mean 1989-1996 tariff change for industries with FDI reform in

Figure B.1: Distribution of Tariff Changes vs. Delicensing and FDI Reforms

(a) Industrial Delicensing (b) FDI Reform



Notes: sub-figure (a) shows a kernel density plot of 1991-1997 tariff changes at the 3-digit industry-level, separately for industries which were delicensed and 1991 and industries which were not delicensed in 1991. Industries which were not delicensed in 1991 were either previously delicensed in 1985 or not yet delicensed by 1997. Sub-figure (b) shows a kernel density plot of 1991-1997 tariff changes at the 3-digit industry-level, separately for industries in which there some opening up to FDI in 1991 and industries which in which there was no opening up to FDI in 1991. In both sub-figures, the mean 1991-1997 tariff changes are shown as vertical lines for each set of industries. All data for these figures comes from the replication package of Aghion et al. (2008).

dig deeper, in Figure B.1 we plot the kernel density of the distribution of tariff changes (at the 3-digit industry-level) separately for industries which were delicensed in 1991 vs. not, and for industries which underwent FDI reform in 1991 vs. not. It is clear that the distribution of tariff changes is very similar for industries that were or weren't delicensed in 1991. Dispersion in tariff changes was slightly higher for industries which underwent FDI reform in 1991, but the average change was very similar. Given the source of bias we are concerned about is that industries with particularly large or small tariff declines were also more prone to be experiencing other reforms, these results reassure us that these other reforms are unlikely to be biasing our empirical elasticity estimates.

1991 was -77.7%, compared to -80.7% for industries without FDI reform.

B2. Impact of Quality Bias on Estimates of θ

If tariff reductions induce firms to improve product quality in ways that are not perfectly captured by the Wholesale Price Index, this might introduce a bias in the IV estimates. To understand the direction and magnitude of this bias, it is helpful to consider a simple case where the elasticity of substitution θ is estimated between two inputs j and k. Denote p^j and p^k the measured input prices for plant i (we omit subscripts i for exposition), and κ^j and κ^k the unobserved quality term. True quality-adjusted prices are therefore given by p^j/κ^j and p^k/κ^k. The elasticity of substitution is estimated as in Equations 3 and 4, with relative tariff changes $\Delta(\tau^j - \tau^k)$ used to instrument for relative price changes $\Delta(p^j - p^k)$. The IV estimate of θ is then given by:

$$\hat{\theta}^{IV} = \theta - (\theta - 1)\frac{\text{Cov}[\Delta ln(\kappa^j/\kappa^k), \Delta(\tau^j - \tau^k)]}{\text{Cov}[\Delta ln(p^j/p^k), \Delta(\tau^j - \tau^k)]} \tag{11}$$

The bias term depends on the covariance of *unmeasured* relative quality changes and tariff changes relative to the covariance of *measured* relative price changes and tariff changes. If tariff changes do not systematically affect unmeasured quality, then the bias is 0. However, if θ is greater than one and tariff reductions induce quality upgrading, then the IV estimate of θ is upward biased. Intuitively, quality upgrading leads us to *understate* the decline in quality-adjusted prices due to the trade liberalization, and for a given change in observed expenditure shares, this leads us to *overstate* the elasticity of substitution.

In order to quantify the potential magnitude of this bias for our estimation, we rerun our baseline IV estimation of θ with simulated quality-adjusted price data. The simulated quality-adjusted plant input prices are constructed as $\Delta\text{ln}\tilde{P}_k = \Delta\text{ln}P_k + \text{x} \cdot \Delta\tau_k$, where x captures the magnitude of the unmeasured quality change induced by tariff reductions. We first consider a case where the unmeasured or residual quality response to tariffs amounts to 10% of the observed price response to tariffs, which is 12.8% (see Table 2). This magnitude of a quality bias would imply that the true elasticity of substitution θ is 2.92, as opposed to the 3.11 which we estimate. A quality response to tariffs 50% as large as the observed price response to tariffs would imply that the true elasticity of substitution is 2.40. Finally, suppose that the quality response to tariffs was as large as the observed price response. Note that this would imply that the true change in prices induced by the trade liberalization was twice as large as the change in prices measured by the Wholesale Price Index. We find that in this case, the true elasticity of substitution is still clearly larger than 1, at 2.05.

C Model Appendix

C1. Model Fit

Before running counterfactuals, we evaluate the 'goodness of fit' of the model. Our model is exactly identified - we match the sector-level and plant-level moments in the baseline year of the ASI/WIOD perfectly. To assess how well it does at predicting aggregate effects of changes in sectoral TFP and revenue distortions, we consider the following excercise: Using our model calibrated to 1995 values, we compare model predictions for the relative growth of different sectors 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. We hold all other parameters at their 1995 calibrated values: preferences, number of plants, plant production parameters and import prices.

We construct 10-year TFP growth rates from the WIOD as follows:

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

ΔQ_s, ΔL_s, ΔK_s, ΔZ_{sk} are the 10-year growth rates of sectoral output, labor, capital and intermediate inputs. γ_s, α_s and $\bar{\pi}_k^z$ are average cost shares.[49] 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.[50] 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 sector-specific factors. 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 intermediate 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 ($\theta = 0.1$), a second 'Cobb-Douglas' calibration in which intermediate inputs are Cobb-Douglas ($\theta = 1$) and a third 'substitutes' calibration with our estimated elasticities ($\theta = 3$). We calculate the 10-year growth rates of the size of each sector, measured as their sales. Since the focus of the paper and the main mechanism we are exploring relates to intermediate input use, we also report the change in each sector's importance as an intermediate input in the economy. Table C.1 shows the correlations between these growth rates in the model and in the

[49] Sector-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.

[50] Among other interpretations, changes in revenues / costs could reflect changes in markups.

data. The correlations are lower than one in all columns, indicating that changes over

Table C.1: Correlation between Growth Rates in Model and in Data

	Complements	Cobb-Douglas	Substitutes
Sectoral Sales	0.056	0.114	0.153
Share of Aggregate Intermediates	-0.597	-0.350	0.315

Notes: The results in the table show the correlation between model and data sectoral growth rates for the variable shown in the left-most column. The first column is the complements calibration, where $\theta = 0.1$. The first column is the Cobb-Douglas calibration, where $\theta = 1$. The third column is the substitutes calibration, where $\theta = 3$.

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.[51] Our results show that the substitutes calibration implies a much higher correlation with the observed growth in the size of various sectors. Importantly, only when calibrated to our estimated elatsicities does the model correctly predict that sectors who have seen their TFP grow have also become more important as intermediate inputs. The correlation between changes in the share of aggregate intermediates in model and data is 0.32 with our baseline calibration, but is negative in both the Cobb-Douglas calibration (-0.35) and the complements calibration (-0.60).

C2. Sources of Heterogeneity in TFP Gap Counterfactuals

When the TFP gap is small, intermediate input elasticities do not matter as much. The reason for this closely relates to Hulten's theorem (Hulten (1978)) which states conditions under which the first-order impact of a sectoral TFP shock is simply the sector's sales share of GDP, regardless of the model elasticity values. Though our model does not fit Hulten's conditions (the model features trade in intermediate inputs and the equilibrium is not efficient), we quantitatively find that the aggregate impact of a small sectoral TFP shock is not very sensitive to intermediate input elasticities. However, higher order terms become more important for larger TFP shocks.[52] We show this in the first panel of Figure C.1, where we plot the ratio of the gains from closing TFP gaps under the substitutes calibration and the complements calibration against the TFP gap. The larger the TFP gap, the larger the relative gains under our substitutes calibration.

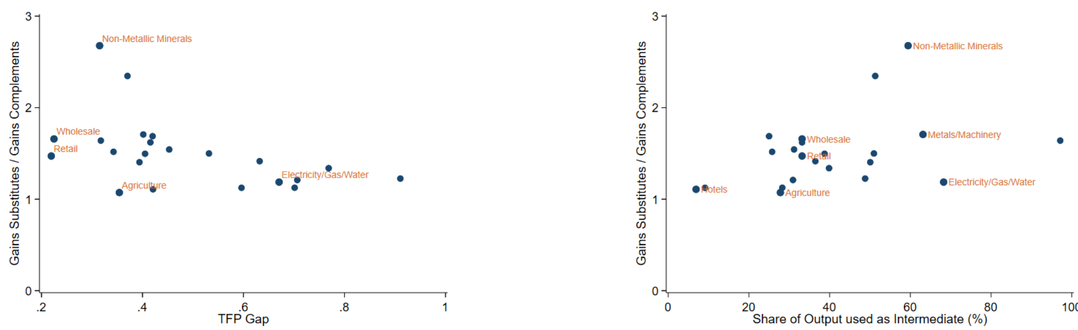
The second source of heterogeneity across sectors is the share of output that is used as an intermediate input. If a sector's output is used entirely in consumption, changes

[51] Measurement error in the WIOD data could also worsen our model fit.

[52] These higher order terms are explored in detail in Baqaee and Farhi (2019), who also provide a second-order approximation to the aggregate impact of sectoral productivity shocks. Baqaee and Farhi (2020b) also extend the first-order Hulten's Theorem terms to inefficient economies.

in that sector's productivity does not affect the relative price of intermediate inputs. The aggregate impact of a sectoral TFP increase therefore does not depend on intermediate input elasticities. In the right panel of Figure C.1, we plot on the x-axis the share of a sector's output used as an intermediate input, and on the y-axis the importance of intermediate input substitution for that sector. We measure this as the gains from closing TFP gaps in the substitutes calibration relative to the Cobb-Douglas calibration. There is a clear positive relationship, showing the importance of this channel in explaining heterogeneity in the importance of intermediate input elasticities.

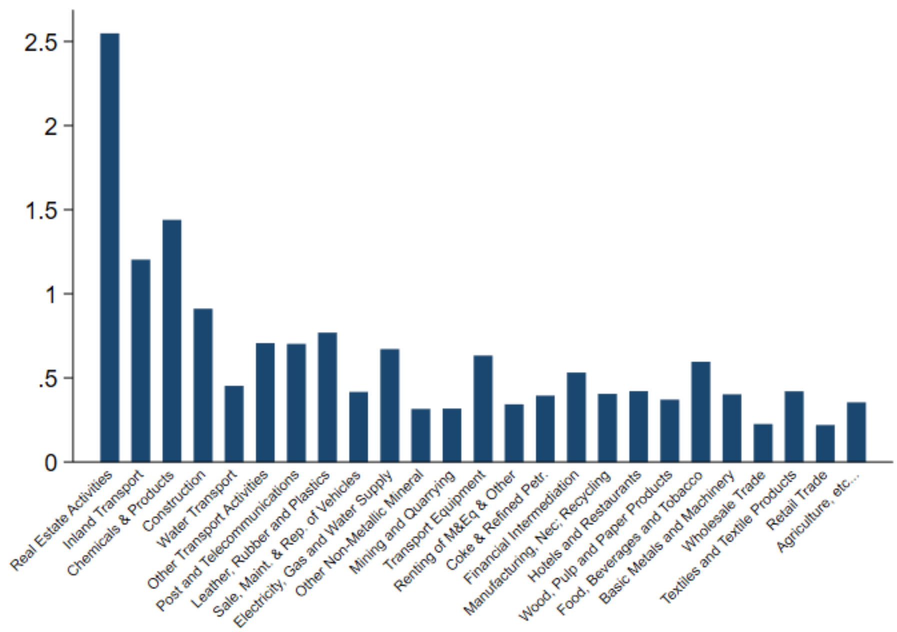
Figure C.1: Sources of Heterogeneity in Across Calibrations



Notes: The y-axes in both panels of this figure show the ratio of GDP gains from closing TFP gaps in our substitutes calibration relative to the complements calibration. The x-axis on the left panel plots the sectoral TFP gap between India and the U.S. The x-axis on the right panel plots the share of a sector's output that is used as an intermediate input.

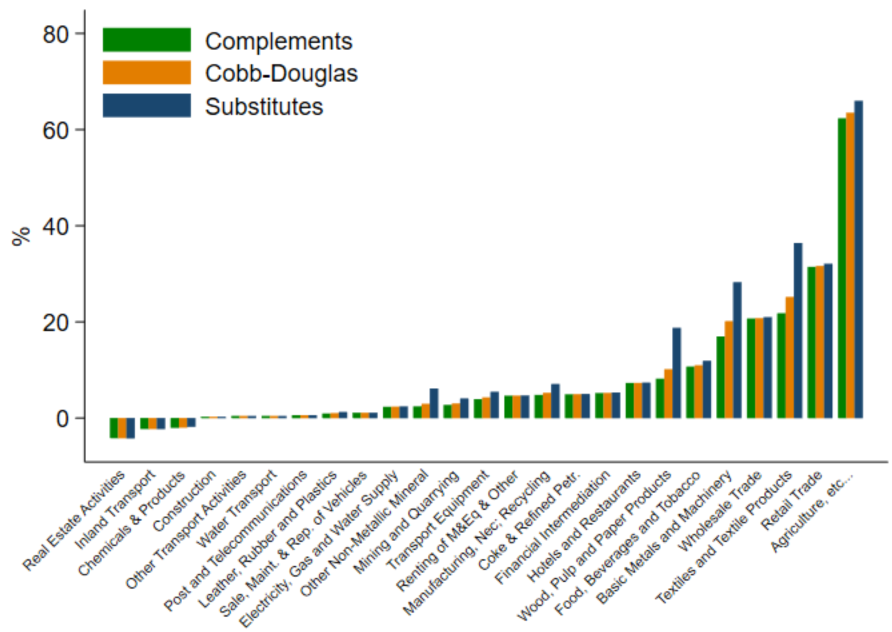
C3. Alternative Calibrations for Counterfactuals

Figure C.2: TFP Gaps



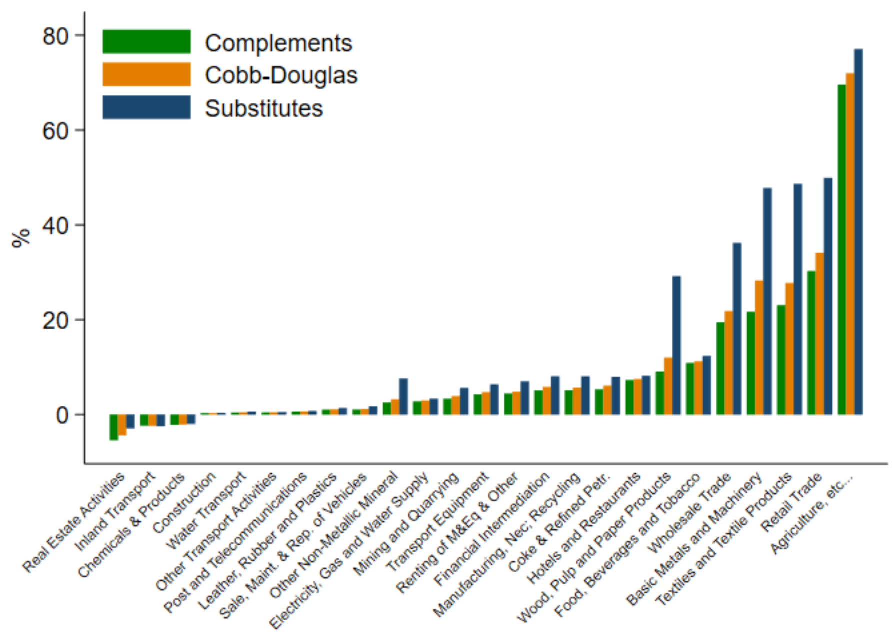
Notes: This figure shows the ratio of India to U.S. sectoral TFP each WIOD sector. A value of 0.5 indicates that Indian TFP is half as large as U.S. TFP in that sector.

Figure C.3: Gains from Closing TFP Gaps, $\theta^E = \theta^S = 1$



Notes: This figure shows the model % GDP gains from closing the India-U.S. sectoral TFP gap of the sector shown in Figure C.2. Each column corresponds to a different calibration of the model. The first column is the Complements calibration, where $\theta = 0.1$. The second column is the Cobb-Douglas calibration, where $\theta = 1$. The third column is an alternative Substitutes calibration, where $\theta = 3$.

Figure C.4: Gains from Closing TFP Gaps, $\theta^X = \varepsilon^S = 1$



Notes: This figure shows the model % GDP gains from closing the India-U.S. sectoral TFP gap of the sector shown in Figure C.2. Each column corresponds to a different calibration of the model. In all calibrations, $\theta^X = \varepsilon^S = 1$. The first column is the Complements calibration, where $\theta = 0.1$. The second column is the Cobb-Douglas calibration, where $\theta = 1$. The third column is an alternative Substitutes calibration, where $\theta = 3$.

Table C.2: Counterfactuals under two alternative calibrations

	$\theta^S = \theta^E = 1$			$\theta^X = \varepsilon = 1$		
	Compl	C-D	Subst	Compl	C-D	Subst
Trade Liberalization	2.17%	2.23%	2.37%	2.40%	2.50%	2.73%
Across and Within Industry (τ_{ij} = 0)	15.3%	15.7%	16.7%	17.1%	17.9%	20.3%
Within Industry (τ_{ij} = τ_j)	11.6%	11.7%	11.9%	12.4%	12.6%	13.1%
Across Industry (τ_j = 0)	0.12%	0.23%	0.62%	0.11%	0.24%	0.69%
Across Inputs ($\tau_{ji}^k \neq 0$)	-3.52%	-5.71%	-12.7%	-2.9%	-7.8%	-37.9%

Notes: This table shows results from the counterfactuals as described in Section 6.1.. The first three columns show the result when we set the between-energy and between-services elasticities to one, and vary only the between-materials elasticity that we directly estimated. The last three columns show the results of varying the between elasticity (θ) as in the baseline case, but setting the upper level elasticities - between energy, materials and services and between value-added and intermediates to one.

C4. 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.[53] 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.[54]

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 $P_{ij} = P_i Q_i^{\frac{1}{\eta}} Q_{ij}^{-\frac{1}{\eta}}$.[55] The industry price index is given by $P = \left(\sum_{i=1}^{N} P_i^{1-\mu} \right)^{\frac{1}{1-\mu}}$.[56] Plants produce each variety Q_{ij} using two inputs A and B and the following production function:

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

[53] This interpretation would only work if different products require different input spending shares.

[54] The 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.

[55] The 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, Redding and Weinstein (2016).

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

$\xi = 0$ 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 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.

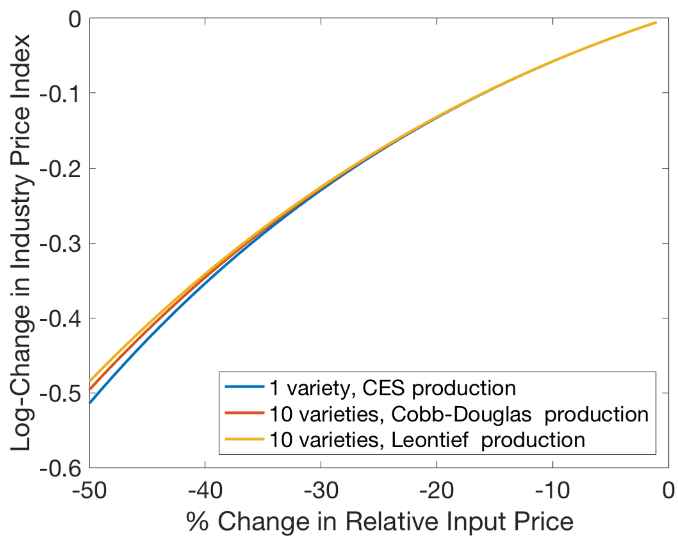
All three researchers observe that the average relative spending share on input A across plants increases by 20% in response to a decrease in the relative price of input A by 6.25%.[57] Researcher 1 infers that $\xi = 4.3$, Researcher 2 infers that $\eta = 11.7$ and Researcher infers that $\eta = 14.0$. 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 C.5 and C.6.

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

[57]This 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%.

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.[58] 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.

Figure C.5: Change in Industry Price Index



[58] The 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 C.6: Change in Industry Spending Share