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, when considering shorter time horizons or more transitory shocks to relative prices, we find evidence of much lower elasticities. Using our long-run elasticities in a quantitative model, we find that misallocation of intermediate inputs causes a reduction in aggregate output of 28%—3.5 times larger relative to a standard calibration with complementary inputs.

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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 sectoral subsidies or 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 2.5 between eight broad categories of material inputs over a 7-year horizon. What differentiates our setting is that plants faced a *permanent* rather than *transitory* change in relative prices and had up to 7 years to adapt their input mix. In contrast, for both shorter time horizons and more transitory shocks to relative prices, we estimate elasticities below one, consistent with similar short-run estimates in the literature (Atalay, 2017; Barrot and Sauvagnat, 2016; Boehm, Flaaen and Pandalai-Nayar, 2019; Carvalho, Nirei, Saito and Tahbaz-Salehi, 2020).

We show that the higher degree of substitutability we estimate over the long run changes the answer to several policy questions substantially. Using a multi-sector model calibrated to India, we find that the economy is more resilient to sector-specific negative TFP shocks relative to a scenario in which intermediates are complements. On the other hand, input distortions are 3.5 times more damaging, and sectoral subsidies cause losses up to 5 times as high, especially if targeted towards intermediate inputs.

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. The main elasticity we estimate is between 8 broad categories of materials, such as Metals, Rubber and Plastics, and Wood and Paper Products.

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. India's trade liberalization is an ideal setting because it was large, unexpected, and without much scope for lobbying or political interference (Topalova, 2010; Irwin, 2025). 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 prices of domestic inputs. We construct a shift-share instrument at the plant level, exploiting the fact that plants used detailed sub-categories of material inputs with varying intensities and, therefore, saw different price changes for each of the eight broad categories of materials. Our identification assumption relies on the quasi-randomness of tariff changes, thereby falling into the "exogeneity of the shifts" category of shift-share IVs (Borusyak, Hull and Jaravel, 2022). We corroborate this assumption with balance tests, which confirm that tariff changes were uncorrelated with industry characteristics or pre-trends.

Our estimate of the plant-level elasticity of substitution between material input categories is 2.5. The 95% confidence interval – [1.5, 3.4] – lies significantly above the Cobb-Douglas benchmark. 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 and attenuation bias. This finding survives a battery of robustness checks concerning the timing of tariff changes, trends in input use, the presence of other reforms (industrial delicensing and FDI), quality upgrading, and many sampling and measurement concerns.

The two notable features of our setting are the long time horizon and the permanence of the shock affecting input prices. These features are especially important in the presence of adjustment costs, which would lead firms to be slow to adjust production processes, especially in response to temporary changes. To gauge whether adjustment costs might explain why existing short-run elasticity estimates tend to be lower than those we estimate, we estimate two additional, short-run elasticities. First, using a subset of inputs whose tariffs changed early during India's trade liberalization, we estimate the elasticity between materials in response to the same permanent shock for a shorter horizon. We estimate an elasticity below one, consistent with evidence that elasticities increase with the time horizon (Boehm, Levchenko and Pandalai-Nayar, 2022). Second, we use fluctuations in global commodity prices, arguably more transitory shocks, to estimate the same materials elasticity over a 1-year horizon. Again, we find an elasticity below one. Taken together, these findings are indicative that manufacturing plants face sizeable convex adjustment costs.

India's trade liberalization constitutes an ideal setting to estimate many long-run elasticities of substitution. We estimate two additional elasticities consistent with the KLEMS classification between energy, materials, and services and between a capital-labor (value added) bundle and an intermediate input bundle. In both cases, we estimate elasticities below one. We also consider a range of other long-run material input elasticities, such as materials vs. labor and materials vs. energy, which we estimate to be close to Cobb-Douglas. Lastly, we estimate the industry-level elasticity of substitution between material inputs, which we find to be slightly higher than the plant-level elasticity.

To gauge the aggregate importance of intermediate input substitutability, we embed our estimates into a canonical multi-sector model calibrated to the Indian economy. We start by simulating large, sectoral TFP drops. In the short run, when intermediates are complements, such a sectoral shock causes a drop in aggregate output of nearly 4% on average. In contrast, when firms can more easily substitute away from inputs from the affected sector, the economy is more resilient, and aggregate output falls by less than 3% on average. We further show that the gains from India's trade liberalization are 5% larger when intermediates are substitutes.

The flip side is that any policy that introduces distortions to firms' intermediate input use can cause substantial harm. We illustrate this in two counterfactuals. First, we simulate the economy with input distortions that represent, for example, different prices charged by upstream suppliers. This causes GDP losses of 28%—3.5 times as large as in an economy with complementary inputs. Second, we simulate a 30% subsidy to one sector's output. Again, losses are much larger in a more flexible economy, amounting to over 4% of GDP with substitutes versus less than 1% with complements.

Related Literature Our paper speaks to a broad literature seeking to unbundle the firm production function using external instruments (Griliches and Mairesse, 1998). We focus on the elasticity of substitution between inputs in production, which, as famously pointed out by Diamond and McFadden (1978), cannot be separately identified from technical change using time series data alone.[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, permanent variation in material input prices. Short-run elasticities between material inputs or material suppliers have been estimated at the firm-level (Adao, Carrillo, Costinot, Donaldson and Pomeranz, 2022; Barrot and Sauvagnat, 2016; Carvalho et al., 2020; Fujiy, Ghose and Khanna, 2023) and industry-level (Atalay, 2017; Miranda-Pinto, 2021).[2] The estimates range between 0 and slightly above 1, in line with our short-run elasticity estimates.

Existing estimates are important inputs for models focused on short-run horizons, such as Bachmann, Baqaee, Bayer, Kuhn, Löschel, Moll, Peichl, Pittel and Schularick

[1] There is an extensive literature in macroeconomics and trade using various identification strategies to estimate elasticities of substitution, such as between domestic and imported materials (Boehm et al. (2019); 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 (2023), Doraszelski and Jaumandreu (2018)).

[2] Another related literature identifies elasticities of substitution between suppliers using model-based indirect inference (Huneeus, 2018; Bernard, Dhyne, Magerman, Manova and Moxnes, 2022).

(2022) who evaluate how the German economy would adjust to a stop of energy imports from Russia.[3] 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 on development.[4] Our findings are particularly relevant for the macroeconomic literature evaluating the impact of distortions to intermediate inputs, such as contracting frictions (Boehm, 2022; Oberfield and Boehm, 2020), transport costs (Peter and Ruane, 2022), industrial policies (Liu, 2019) and heterogeneous supplier prices (Burstein, Cravino and Rojas, 2024).

Our paper fits into a literature that emphasizes differences between short-run and 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 et al. (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. Hassler, Krusell and Olovsson (2021) model how directed technical change results in higher effective long-run elasticities between energy and other inputs.

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)), markups (De Loecker, Goldberg, Khandelwal and Pavcnik (2016)) and investment prices (Johri and Rahman, 2022). 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.

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

[3]Baqaee and Farhi (2019, 2020, 2024) derive second-order approximations for the aggregate impact of business cycle shocks, the impact of distortions, and changes in trade barriers. The elasticity of substitution between materials is a key parameter in these approximations.

[4]Jones (2011) explores the importance of complementarities in production for cross-country development.

data. In Section 4 we show the results from our long-run elasticity estimation. In Section 5 we estimate two short-run elasticities of substitution. Section 6 presents estimates of other important elasticities. Section 7 outlines a quantitative model and presents counterfactual results and Section 8 concludes.

2. Estimating Equations

We aim to estimate the causal response of plant intermediate input use to changes in prices of these inputs. The level of aggregation for our main results is broad categories of material inputs, such as plastics or chemicals. We estimate how spending shares on a given material input k relative to material input j change in response to changes in the relative price of k and j. Consider the following log-linear specification:

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

where $\Delta\ln\left(\frac{E_{ik}}{E_{ij}}\right)$ 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.

If input prices vary exogenously, the coefficient β_m in Equation (1) identifies the local elasticity of substitution between material inputs k and j. If elasticities are independent of the magnitude of the relative price change, such as in a constant elasticity of substitution (CES) framework, β_m identifies *the* elasticity of substitution between material inputs. To be specific, assume material inputs are aggregated into an input bundle M_{it} given by:

$$M_{it} = \left[\sum_{k=1}^{\kappa} \pi_{ikt}^{m} M_{ikt}^{\frac{\theta-1}{\theta}}\right]^{\frac{\theta}{\theta-1}} \tag{2}$$

θ is the elasticity of substitution between the κ categories of material inputs. The plant-specific technologies π_{ikt}^{m} determine the relative weight of each type of material input in production, reflecting different production 'recipes' as in Oberfield and Boehm (2020).

To derive our estimating equations, we only need to assume that plants minimize costs and are input price takers. We impose no assumptions on the demand structure and allow input prices to vary across plants. Taking changes over time from plants' first-order conditions, we have that:

$$\Delta\ln\left(\frac{E_{ik}}{E_i^m}\right) = (1-\theta)\Delta\ln\left(\frac{P_{ik}}{P_i^m}\right) + \theta\Delta\ln(\pi_{ik}^m) \tag{3}$$

where E_i^m is total expenditures on materials, and P_i^m is plant i's material input price index.[5]. In the Cobb-Douglas benchmark where $\theta = 1$, expenditure share changes are independent of price changes. If substitutability is higher (lower) than Cobb-Douglas, price increases cause a decrease (increase) in expenditure shares.

Equation 3 is the structural equation we take to the data. Estimating these parameters requires data on plant-level intermediate input expenditures, data on input prices and 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 liberalization as an instrumental variable when estimating these equations in 2SLS. We discuss the setting and data next.

3. Empirical Setting and Data

In this section, we first describe India's trade liberalization and argue that it constitutes a natural experiment that is uniquely suited to estimating 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, high import tariffs, and 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, the sudden 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

[5]This is given given by $P_i^m = \left(\sum_{k=1}^{\kappa}(\pi_{ik}^m)^\theta P_{ik}^{1-\theta}\right)^{\frac{1}{1-\theta}}$

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

on a program of major structural reforms.

A major component of these reforms was opening up to trade, which was implemented as part of India's Eighth Five-Year Plan between 1992 and 1997. The trade liberalization had two goals: 1) a reduction in average tariff levels and 2) a harmonization of tariff levels across goods. Average Indian import tariffs declined from 80% down to 30% between 1991 and 1997 (Figure 1a). At the same time, the dispersion in tariffs fell from 39.4% to 14.5%. Non-tariff barriers on intermediate inputs were also reduced rapidly in the first few years of the trade liberalization (Topalova and Khandelwal, 2011; Irwin, 2025) .

Given the goal of harmonization, the decline of any given tariff is well predicted by its initial level in 1991(Figure 1b). The initial level of tariffs was set during the Second Five-Year Plan (1956-1961). There was significant hysteresis in India's trade policy until the crisis in 1991 (Gang and Pandey, 1996); import restrictions remained even as the structure of industry evolved. This feature of India's history renders tariff reductions quasi-random.

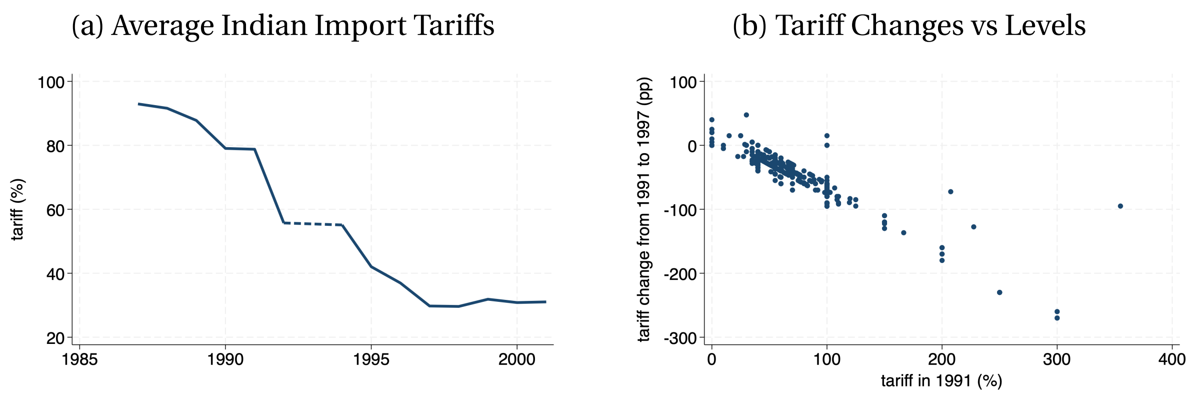
Furthermore, the 1991 crisis was both sudden and unexpected. As a result, the trade liberalization was pushed through rapidly and without much scope for industry lobbying (Hasan, Devashish and Ramaswamy, 2003; Goyal, 1996; Varshney, 2000; Irwin, 2025).[7] This gives us confidence that any remaining heterogeneity in tariffs was not driven by (expected) conditions in individual sectors.

Balance Tests To further check that the tariff changes constitute a quasi-random shock, we show in Table B.4 that neither pre-reform industry characteristics (such as size or capital intensity) nor pre-reform industry trends (in prices, size or TFP) are correlated with the post-reform changes in industry input or output tariffs.[8] We also show in Appendix B that tariff changes were not correlated with the FDI reforms and industrial delicensing that occurred during the early 1990s. The distribution of tariff changes between 1991 and 1997 is very similar for industries that did and didn't experience other reforms (Figure A.1), with the difference in average tariffs both small and statistically insignificant.

[7] Irwin (2025) describes how the extent of the reforms largely came as a surprise: "Congress's 1991 election manifesto gave little hint that sweeping reforms were in store, let alone a dismantling of Nehruvian socialism." Due to the crisis and political circumstances, the trade reform was implemented in a matter of hours rather than weeks or months. Given that import liberalization was only one component of a broader package of reforms that were more politically charged (such as cuts in fuel and fertilizer subsidies, as well as industrial delicensing), they received surprisingly little pushback (Irwin, 2025). Tariff reductions were also largely at the discretion of the finance minister and did not require public debate.

[8] This is consistent with similar findings in Topalova (2010) and Topalova and Khandelwal (2011).

Figure 1: Indian Import Tariffs



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 an 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.

3.2. Datasets

Our approach to estimating Equation 3 requires data on how much Indian plants spend on various types of material inputs, the prices they face for these inputs, and the import tariffs imposed on them. This section describes the main datasets we use.

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 (Appendix Table A.1). The survey contains many of the standard measures of output and inputs (sales, labor, capital, materials). 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 distribution of plant-level employment are shown in Appendix Table B.1 and Figure B.1 respectively.

An important feature of the ASI is that plants report expenditures on highly disaggregated categories of material inputs in certain years. Imports and domestic material expenditures are also reported separately for each input category. During our period of interest, this detailed breakdown of material inputs is available for the years 1989, 1993, 1994, and 1996. The data quality unfortunately worsens in the 1997 and 1998 surveys before improving again from 1999 onwards.[9] We, therefore, use the 1989 survey to measure pre-reform material expenditure shares, the 1996 survey to measure post-reform material expenditure shares, and the 1993/1994 surveys to explore transition dynamics from the short to medium-run.

The classification used for the reporting of material input expenditures and quantities in 1996 is 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'. These are further disaggregated into 250 3-digit categories and 5500 5-digit categories. Table A.2 shows the most commonly used material inputs within each 1-digit category. Before 1996, plants report their materials according to the ASI Item Code classification. To link input expenditures between the earlier (1989, 1993, 1994) and later (1996–) waves, we construct a concordance between the ASI Item Code classification and the ASICC at the 5-digit, 3-digit level and 1-digit level. Appendix A provides additional summary statistics and details about the data and concordance.

3.2.2. Tariffs and Prices

We obtain the official Indian import tariffs from Topalova (2010). These are available for 5000 HS6 good categories. We use India's Wholesale Price Index (WPI) to measure prices for domestically produced inputs. The WPI contains yearly prices for 450 product categories covering the main agricultural and mining commodities and the main manufactured products. We complement the WPI with service and fuel price indices from World KLEMS.

We construct a concordance linking our price and tariff data to the ASICC classification at the 5-digit level (see examples in Table A.4). We keep only inputs for which both prices and tariffs are available from 1989 to 1997 and drop a set of goods (mostly cereal grains, oil seeds and derived agricultural products) where imports and exports were restricted to the public sector (canalization). As a result, we obtain price and tariff measures for 495 5-digit ASICC categories.

[9]The main issues are that the size threshold for inclusion in the survey was doubled, while the number of material inputs plants were required to report was capped at 5. In addition, there is a sharp increase in 1998 in the share of materials classified as 'Other'. See Appendix A1. for more details.

4. Estimation of Elasticity of Substitution Between Material Inputs

In this section, we describe the estimation of the plant-level elasticity of substitution between material inputs and present our main results.

4.1. Empirical Specification

OLS estimates of elasticities of substitution might suffer from attenuation and simultaneity bias. Classical measurement error in input prices biases the estimate of θ towards 1. Simultaneity bias could arise from 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 would bias OLS estimates of θ towards 0.

We overcome both of these concerns by instrumenting input price changes with tariff changes. Our empirical specification to estimate the elasticity of substitution between material inputs follows from equation (3):

$$\text{First stage: } \Delta\ln(P_{ik}) = \rho_m \, \Delta\tau_{ik} + \lambda_i + \eta_{ik} \tag{4}$$

$$\text{Second stage: } \Delta\ln\left(\frac{E_{ik}}{E_i^m}\right) = \beta_m \, \Delta\ln(P_{ik}) + \lambda_i + \epsilon_{ik} \tag{5}$$

where i denotes a plant, k is a 1-digit material input category (e.g., Textiles), and Δ stands for changes between 1989 and 1996. E_{ik}/E_i^m 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 price index for material input k. $\Delta\tau_{ik}$ is the change in the import tariff measure for plant i's material input k. λ_i is a plant fixed effect. ρ_m is the elasticity of domestic input prices with respect to import tariffs; the pro-competitive effects of tariff reductions. β_m is one minus the estimate of the elasticity of substitution between materials.

4.2. Variable Construction

We measure aggregate import tariffs and input prices at a granular level, allowing us to use plant-level spending shares to construct *plant-specific* input prices and tariffs at the 1-digit material input level. We now describe this approach.

Input prices. We construct plant-specific changes in 1-digit material input (k) prices as the weighted average change in 5-digit material input (l) prices used by plant i:

$$\Delta\ln(P_{ik}) = \sum_{l} \bar{w}_{ikl} \Delta\ln(P_{kl}) \tag{6}$$

The weights $\bar{w}_{ikl}$ are average (Tornqvist) expenditure shares over the initial and end-period. In particular, for the change in the price index between 1989 and 1996, we construct $\bar{w}_{ikl} = (w_{ikl}^{1989} + w_{ikl}^{1996})/2$. This allows for an extensive margin at the 5-digit level, as the weights can equal 0. The advantage of using a Tornqvist price index over a Laspeyres price index (which uses initial period weights) is that the resulting price index $\Delta\ln(P_{ik})$ is a second-order approximation to the change in the true price index for any constant elasticity production function between 5-digit inputs. We, therefore, do not need to take a stand on how much substitutability there is *within* each 1-digit material input category.

Import tariffs. We construct plant-specific import tariffs at the 1-digit material input level using the same approach as for prices, except that the 5-digit tariff changes are weighted by 1989, rather than average, expenditure shares w_{ikl}^{1989}:

$$\Delta\tau_{ik} = \sum_{l} w_{ikl}^{1989} \Delta\tau_{kl} \tag{7}$$

We weight using initial period shares when constructing the import tariff to avoid post-liberalization expenditures on materials (which we treat as endogenous) entering the instrument (see for example Borusyak, Hull and Jaravel (2024)). The weights w_{ikl}^{1989} sum to one within each k.

Measurement challenges. We face two measurement challenges. Firstly, we do not have prices and tariffs for all 5-digit ASICC inputs (P_{kl} and τ_{kl}). Secondly, we rely on a concordance to the ASICC classification to construct the weights (w_{ikl}) on each 5-digit material input for the 1989-1994 ASI surveys. Due to these two issues, we lose 17% of plant x 1-digit input observations. However, these observations account for only 6% of aggregate material expenditures, so our coverage remains high. We provide more detail on how we construct the price and tariff variables in Appendix A2..

Estimation sample. The estimation sample consists of plants we observe in the ASI in both 1989 and 1996 and which use at least two categories of 1-digit material inputs in both years. The latter restriction comes from the fact that our specification identifies $\hat{\theta}$ from changes in *relative* expenditure shares within the plant. We drop the 1-digit input category "Transport Equipment" as it corresponds more closely to capital than to material inputs. We drop plants that import in either 1989 or 1996 because our identification relies on how import tariffs affect *domestic* input prices. We drop plants that change 4-digit industry as these plants likely changed which products they make. We trim the 1% tails of spending share changes ($\Delta\ln(E_{ik}/E_i^m)$) and price changes ($\Delta\ln(P_{ik})$), as well as the 5% tail of tariff changes ($\Delta\tau_{ik}$). 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.[10] Appendix Tables B.1 and B.2 report summary statistics for the estimation and full samples.

4.3. Identification

Our IV falls into the category of shift-share (Bartik) instruments (Bartik, 1991; Borusyak et al., 2024). Our identifying argument stems from the exogeneity of the many shifts (Borusyak et al., 2022) rather than exogeneity of the shares (Goldsmith-Pinkham, Sorkin and Swift, 2020). In other words, we assume that the variation in tariffs across 5-digit material inputs is quasi-random. We outlined the institutional features of India's trade liberalization which make the tariff variation plausibly quasi-random in Section 3.1.. We also described the balance tests we have run which show that tariff changes are uncorrelated with various other factors potentially leading to shifts in the demand for material inputs.[11] This is a sufficient condition for identification, provided that the shocks are dispersed, large in number, and with sufficiently small average exposure at the plant level.

These conditions are met in our setting. We observe tariffs for 495 material input categories at the 5-digit level, though this falls to 297 tariffs once we restrict to inputs used by plants in 1989. Appendix Figure B.3 plots the distribution of 1989-1996 tariff changes at the 5-digit level, with and without residualizing on 1-digit fixed effects. It shows that the shocks are dispersed—the standard deviation of tariff changes is 41pp in the raw data and 40pp after residualizing. Regarding the third condition, the need for small average exposure at the plant level implies that there must be sufficient heterogeneity in plants' material input expenditures within 1-digit ASICC categories.[12] A notable feature of plant-level data, and the Indian ASI in particular, is the significant

[10] This sets the largest tariff decline at the plant-level to -160pp. In contrast to tariff changes, the distribution of price changes and spending share changes is symmetric. The IV estimates are similar in magnitude with 1% trimming (Table B.11).

[11] In Table B.6 we also check that the import tariff instrument is uncorrelated with other observables at the plant-input level in 1989, including the average price of a plant's inputs in 1989 relative to the industry median, the number of 5-digit inputs used by the plant (within a 1-digit input category), and the share of inputs concorded across classifications.

[12] Our exposure measures sum to 1 by construction, and therefore we do not need to include the "incomplete share" control from Borusyak et al. (2022).

dispersion in expenditures on material inputs even within narrowly-defined industries (see, for example, Appendix Figure B.2 and Oberfield and Boehm (2020)). To see how the distribution of plant exposures affects our estimation, we follow Borusyak et al. (2022) and report summary statistics of tariff changes weighted by their respective importance weights.[13] The importance-weighted standard deviation of tariff changes is 36pp, only slightly down from the unweighted dispersion (see kernel density plots in Appendix Figure B.4). The inverse of the Herfindahl Index of importance weights – the 'effective number of shifts' – is 33. This is significantly smaller than the total number of tariffs because some general-purpose inputs are used by many plants across industries (e.g., "gunny bags" has the largest importance weight). In summary, while the effective number of tariffs is lower than the total number of tariffs, there remains substantial dispersion in tariff changes underpinning our estimation strategy.

4.4. Estimation

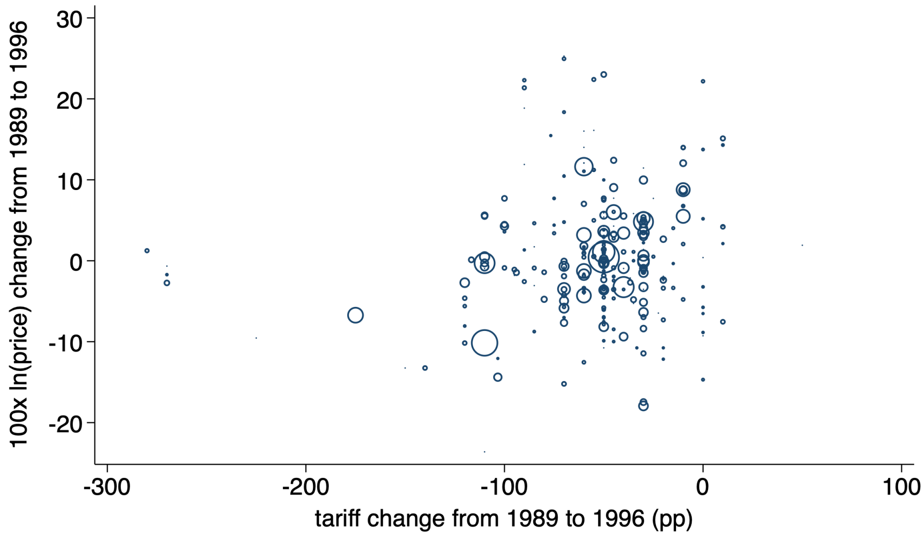
We estimate the first stage regression following Equation 4 and report results in the lower panel of Table 1. For all our first and second-stage IV results, we report exposure-robust standard errors from the equivalent tariff-level instrumental variable regression, following Borusyak et al. (2022). We estimate that a 10 pp (relative) reduction in tariffs reduces (relative) domestic prices by 1.59%. Coincidentally, this is almost identical to De Loecker et al. (2016) 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 18.0, above the conventional threshold of 10. We plot the relationship between tariff changes and input prices non-parametrically in Figure 2. There is no clear evidence of non-linearities in the relationship between tariff changes and price changes.

Why do tariff reductions on imported inputs lead to price falls for the same domestically produced inputs? The main explanation is that tariff reductions increased competition facing domestic producers. As a result, domestic producers reduced their markups or found ways to improve production efficiency. De Loecker et al. (2016) find that markup declines were an important explanation for the pro-competitive effects of India's trade liberalization.

The top panel of Table 1 presents the baseline OLS and IV estimation results. The OLS estimate of θ is 1.3 with a standard error of 0.17. As mentioned previously, both attenuation bias and simultaneity bias should lead to downward biased estimates of θ (the former assuming that $\theta > 1$). In addition, the OLS estimate picks up short-run price fluctuations and the long-run changes induced by tariff reductions. Given that we expect short-run substitution elasticities to be lower than long-run elasticities, this is

[13]The importance weights are proportional to the exposure share of that 'shift' for an average observation.

Figure 2: Pro-Competitive Effects of Tariff Reductions
(Non-Parametric First Stage)



Notes: This figure plots the exposure-share weighted change in Indian input prices against the change in Indian import tariffs between 1989 and 1996, following Equation 4. Each circle corresponds to a 5-digit ASICC product category, weighted using the importance weights from Borusyak et al. (2022). The estimate from the corresponding linear regression is 0.159, with a standard error of 0.038 (also reported in Table 1). See Sections 3.2.2. for details on underlying data sources and variable construction.

another reason why the OLS estimate may lie below the IV estimate.

Consistent with a downward bias for OLS, the IV estimate of θ is higher, 2.5, with a standard error of 0.48. This is economically and statistically significantly higher than the Cobb-Douglas benchmark of 1. The 95% confidence interval lies between 1.5 and 3.4. 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 will lead to the relatively more expensive input's share declining to 47% over time and the relatively cheaper input's share increasing to 53%.

Our estimate of the elasticity of substitution between materials is significantly higher than existing estimates from the literature. We report the closest other estimates of θ in Table 2, alongside the level of aggregation, country and time period, and time horizon over which they are estimated.[14] These estimates vary considerably in the levels of aggregation they consider; Barrot and Sauvagnat (2016), Carvalho et al. (2020), Fujiy et al. (2023) and Adao et al. (2022) estimate a firm-level elasticity of substitution between suppliers while Atalay (2017) and Miranda-Pinto (2021) estimate an industry elasticity of substitution between broad material input categories. The values estimated range

[14]While also important, we do not include in this list papers estimating elasticities of substitution between imported and domestic intermediates (such as Boehm et al. (2019) or Blaum et al. (2019)).

Table 1: Baseline estimate of θ

	OLS	IV
Δln(prices)	-0.30	-1.47
	(0.17)	(0.48)
$\hat{\theta}$	1.30	2.47
	[0.97, 1.63]	[1.53, 3.41]
First Stage		
Δ tariffs		0.16
		(0.038)
F-stat		18.0
Observations	10,144	10,144
# plants	3,943	3,943
# 5-digit ASICC inputs	297	297

Notes: This table shows estimation results from the specifications in equations 4 and 5. An observation is a plant $\times$ 1-digit material input category. 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 at the 1-digit ASICC input level. All regressions include plant fixed effects. Regressions are weighted by the inverse of the number of inputs used by the plant; i.e., each plant is weighted equally. OLS standard errors are clustered at the 4-digit industry level. We report exposure-robust standard errors from the equivalent tariff-level instrumental variable regressions for the first-stage and IV specifications. The inverse of the Herfindahl index of the exposure weights is 33.3, and the largest weight is 0.101.

from strong complementarities to slightly above Cobb-Douglas. While the countries and time periods vary, the common factor across these estimates is that almost all focus on short time horizons of up to 1 year.[15] In contrast, we estimate the long-run elasticity between materials for a time horizon of 7 years in response to a permanent shock to prices. We also provide estimates of short-run elasticities in our setting in Section 5., which we estimate to be more in line with the papers in Table 2.

4.5. Robustness

We perform a variety of robustness checks, which we summarize below.

[15] In addition, these papers cover most sectors of the economy, while our paper focuses on manufacturing. Miranda-Pinto (2021) estimates a higher short-run elasticity between material inputs for service sectors relative to manufacturing.

Table 2: Production Elasticities in the Literature

Paper	Elasticity	Aggregation	Country & Time Period	Horizon	Value
Adao et al. (2022)	b/w suppliers	Firm	Ecuador 2009-2015	1-5 year*	1.36
Atalay (2017)	b/w materials	Industry	U.S. 1997-2013	1 year	-0.1
Barrot and Sauvagnat (2016)	b/w suppliers	Firm	U.S. 1978-2013	1 year	≈ 0
Carvalho et al. (2020)	b/w suppliers	Firm	Japan, 2010-2012	1 year	1.2
Fujiy et al. (2023)	b/w suppliers	Firm	India 2019-2020	1 Month	0.55
Miranda-Pinto (2021)	b/w materials	Industry	U.S. 1997-2018	1 year	-0.1

Notes: This table lists papers estimating the elasticity of substitution between material inputs, or between suppliers of material inputs. The second column specifies whether the elasticity is between supplying firms or between material input categories. The third column specifies if the unit of production considered is the firm or the industry. The fourth column specifies the country and time period considered. The fourth column specifies the time horizon over which the elasticity is estimated. The fifth column reports the point estimate of the elasticity. *We report a 1-5 year horizon for Adao et al. (2022) because their specification pools together both short-run and medium-run variation.

Timing of tariff changes. The ideal scenario in which to estimate the long-run elasticity of substitution between material inputs would be for all tariffs to change simultaneously once and for all. This did not occur during India's trade liberalization. While most products saw their tariffs fall early, a minority of products had large tariff changes late in the liberalization period. This staggered timing introduces potential issues both with the power of the instrument (if pro-competitive effects take time) and with the interpretation of our estimate as a long-run elasticity.

To gauge the importance of this concern, we re-estimate θ under additional sampling restrictions. First, we drop plant-inputs-pairs that experienced relatively large and late tariff changes, defined as a decline in tariffs greater than 20pp between 1994 and 1996 that accounted for at least 50% of the overall tariff decline from 1989 to 1996. Secondly, we also restrict our attention to plants that saw large (relative) tariff changes in the very first years of the liberalization; plants with above median standard deviations of 1989-1992 tariff changes across their inputs. Reassuringly, we find very similar results to our baseline (Table B.7).

Trends in input use. The balance tests in Table B.4 indicate that tariff changes were not correlated with industry trends prior to the liberalization. We can go further and control for any trends in input use occurring at the 1-digit ASICC level during the liberalization by adding 1-digit ASICC fixed effects to Equation 4 and Equation 5. This rules out the possibility that our results are driven by trends in input use or input prices that happened to be correlated with tariff changes. We report the results in Table B.7. The first-stage estimates are very similar, while the IV estimates are somewhat larger in magnitude (above 3) and have larger standard errors but remain statistically significantly different from 1 at the 10% level.

Other Reforms We reported in Section 3.1. that both industrial delicensing and FDI reforms were uncorrelated with tariff changes. Still, plants in industries experiencing other large reforms may have had different responses to tariff changes, which could have implications for external validity. To test whether this is the case, we report in Table B.8 the elasticity estimates separately for industries that underwent other reforms between 1991 and 1997 and those that didn't. As before, we consider two of the other major sets of reforms that occurred during this period: industrial delicensing reforms and FDI reforms. We find that point estimates tend to be larger for plants in industries that did *not* undergo simultaneous reforms, while standard errors are considerably larger for plants that did undergo other reforms. One explanation for this is that delicensing may have significantly changed the products plants produced, introducing measurement error through changes to the input bundles that were not related to tariff changes. Reassuringly, this suggests that our estimates would also be applicable to other empirical settings where plants only faced changes in relative prices.

Import substitution and quality upgrading. There may be a concern that reductions in import tariffs may induce domestic producers to improve the quality of their products (Verhoogen, 2008; Goldberg et al., 2010; Bas and Strauss-Kahn, 2015). To the extent that these quality changes are not perfectly captured by the Wholesale Price Index (as discussed in Section 3.2.2.), they might introduce a bias in the IV estimates. While India's statistical authorities designed the WPI to track goods of constant quality, 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).[16] We evaluate the potential direction and magnitude of this bias in Appendix C. 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 2.3, declining to 2.0 if the unmeasured quality upgrades are as high as 50% of observed price responses. These results suggest that, even for very large unmeasured quality changes induced by tariff changes, the true elasticity of substitution remains high.

Sampling and Firm Exit Our estimation strategy limits us to plants that we observe both in 1989 and 1996. Because only plants with more than 100 workers are sampled with certainty, and because smaller plants typically have higher exit rates, large formal manufacturing plants are over-represented in our estimation sample relative to smaller

[16]According to the documentation, statistical authorities were well aware of issues related to quality and variety changes over time. 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.

ones (see Figure B.1 and Table B.1).[17]

Plants of different sizes could have different elasticities of substitution for several reasons. On the one hand, production flexibility could reflect good management and, therefore, be 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 estimate somewhat higher elasticities for smaller plants, 2.9 vs. 2.2, though the difference is not statistically significant (Table B.10).

Further, in order to be in our estimation sample, a 1-digit input must be used by the plant in both 1989 and 1996. Our baseline estimation strategy, therefore, does not capture extensive margin changes at the 1-digit level. For example, plants could switch from cardboard/paper to plastic containers and drop the 1-digit category 'Wood, Cork and Paper' entirely. However, the 1-digit inputs that get dropped or added typically account for a very small share of plant expenditures. At this level of aggregation, the median value-share of inputs dropped (added) is 1.6% (1.1%) (Table B.3). We also conduct a robustness check in estimating θ for plants where there is no extensive margin change in the set of 1-digit inputs used between 1989 and 1996 (Table B.9). We estimate an elasticity very similar to the baseline.

The last concern is that the trade liberalization led to differential plant exit. For instance, one may think that plants with less flexible production processes were less well able to adapt to import competition and shut down as a result. If this is the case, our estimation sample consist of firms with higher elasticities of substitution. While our setting offers limited possibilities to address this directly, we can gauge the importance of this channel by comparing our plant-level estimates to the *industry-level* elasticity of substitution between material inputs, which we estimate in Section 6.3.. This elasticity, which captures the effects of plant entry and exit on changes in industry expenditure shares, is broadly in line with our baseline estimate of θ.

Measurement Lastly, we show that our results are robust to the way we clean and trim the data, as well as alternative methods of constructing the price and tariff measures (Table B.11).[18] We also consider additional robustness exercises in Table B.9. We find

[17] In addition, our sample does not include any *informal* manufacturing plants; these account for roughly 35% of manufacturing value-added during the 1990s (Bollard, Klenow and Sharma, 2012).

[18] We consider the following robustness checks: 1) only trimming the 1% tails of tariff changes, 2) trimming the 2% tails of prices, tariffs, and shares, 3) using average industry value shares to construct the price and tariff variables instead of plant-specific shares, 4) constructing prices and tariffs using plant-specific 3-digit expenditure shares but aggregate 5-digit expenditure shares within each 3-digit category, 5) restricting the sample to plants where more than 95% of inputs in 1989 are concorded to the ASICC

similar results to the baseline when we use a Laspeyres price index (using 1989 shares as weights) when restricting the sample to each plant's top three inputs or restricting the set of inputs to those that account for at least 1% of plant expenditures (averaged between 1989 and 1996).

5. Short-Run vs. Long-Run Elasticity Estimates

The high elasticity of substitution we estimate contrasts significantly with existing, much lower estimates (Atalay, 2017; Barrot and Sauvagnat, 2016; Boehm et al., 2019; Carvalho et al., 2020). There are three aspects that are unique to our setting. First, we estimate elasticities over a longer horizon, seven years, rather than quarter on quarter or year on year. Second, the trade liberalization constitutes a permanent shock to relative prices rather than a change that is likely to be temporary, such as supply chain disruptions. Both of these differences are especially important in the presence of adjustment costs, which would lead firms to be reluctant to adjust production processes quickly or in response to temporary changes. Third, we estimate elasticities for Indian firms rather than firms in advanced economies such as the U.S. or Japan.

To gauge the importance of the time horizon and the perceived permanence of the price change, we estimate two additional, short-run, elasticities in this section. First, using the subset of inputs whose tariffs changed early, we estimate the elasticity between materials for a shorter horizon. While standard errors are large, we find suggestive evidence that elasticities increase with the time horizon, consistent with (Boehm et al., 2022). Second, we use transitory shocks (fluctuations in global commodity prices) to estimate the same elasticity over a 1-year horizon. We find much lower elasticities, closer to the conventional wisdom in the literature.

5.1. Dynamics Effects of Trade Liberalization

We use the 1993 and 1994 waves of the ASI to estimate the short-run elasticity of substitution between material inputs and contrast the results with the long-run estimates from the 1996 wave of the ASI.

The reductions in tariffs across product lines were staggered between 1991 and 1997; some products saw their tariffs fall earlier than others. Tariff rates were at the discretion of the minister for finance, and so did not require public debate (Irwin, 2025), and beyond a gradual lowering of the maximum tariff rate (Singh, 2017), it is not entirely clear

classification, 6) constructing tariff changes as $\ln(1+\tau_{ik})$. The only case where the IV estimate is not significantly greater than 1 is when we use average industry value shares to construct prices and tariffs. The lower precision is not surprising as we use less of the available variation in the data.

how policymakers determined the sequencing of tariff reductions. While the sequencing of tariff reductions could in principle reflect strategic industry considerations or lobbying, 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'*.[19] This suggests that the sequencing of tariff changes throughout the trade liberalization was not driven by a development strategy or lobbying linked to trends in material input use. Corroborating this, we re-run balance tests in Table B.5 and confirm that the tariff changes from 1989 to 1992 are not statistically significantly associated with industry characteristics in 1988 or pre-trends from 1985 to 1988.

The short-run estimation sample comprises plant-inputs from our baseline estimation in Section 4. that also are sampled in either 1993 or 1994. This ensures that differences between our short-run and long-run estimates are not driven by plant exit or changes in the extensive margin of input use. We also make the same sampling restrictions as for our robustness check in Section 4.5.; we only keep plants that experienced large relative tariff changes in the first year of the liberalization, and drop any plant-inputs where there were large tariff changes between 1994 and 1996.[20] This ensures that plants in the short-run estimation sample already experienced meaningful tariff changes by 1993/1994.

The identifying assumptions remain the same as described in Section 4., though the estimation sample and period are now different. To check that the sample restrictions are not meaningfully changing the composition of the sample, we show in Figure B.5 that the distribution of plant sizes and material expenditure shares in 1989 are similar for plants that are in the short-run estimation sample and those that are only in the long-run estimation sample.

The estimation equations are similar to those for our baseline specification, except they are now indexed by a year subscript t, given that we pool together 1993 and 1994:

$$\text{First stage: } \Delta \ln(P_{ikt}) = \rho_m \, \Delta\tau_{ikt} + \lambda_{it} + \eta_{ikt} \tag{8}$$

$$\text{Second stage: } \Delta \ln\left(\frac{E_{ikt}}{E_{it}^m}\right) = \beta_m \, \Delta \ln(P_{ikt}) + \lambda_{it} + \epsilon_{ikt} \tag{9}$$

Because we are pooling two years of data, the plant fixed effects are replaced with plant$\times$year

[19] Topalova (2010), with full interview available here: https://www.rediff.com/money/2004/jul/05inter.htm)

[20] For the first restriction, we regress the 1989-1992 tariff changes at the plant-input level on a plant-fixed effect, and construct the standard deviation of the residuals. We only keep plants with above median standard deviation of the residuals. For the second restriction, we drop plants that experienced a decline in tariffs greater than 20pp between 1994 and 1996 that accounted for at least 50% of the overall tariff change.

fixed effects. As before, we report exposure-robust standard errors from the equivalent tariff-year level IV regression, clustered at the 5-digit ASICC level.

We present short-run results in Table 3. We also present the long-run estimates under the same sampling restrictions for comparison. The short-run first stage is somewhat weaker than for the corresponding long-run estimation; the F-stat is 17. We also find lower pro-competitive effects of tariff reductions on domestic input prices relative to the longer time horizon. Our interpretation is that the pro-competitive effects of trade also take time to materialize; low-productivity firms may not immediately exit, and it may take time for imported inputs to penetrate all markets. The OLS and IV estimates of the short-run elasticity of substitution are all less than one. We cannot reject Cobb-Douglas, and in the case of the IV estimates, we can neither reject Leontief or elasticities as high as 1.9 with 95% statistical confidence. In contrast, the long-run estimates are all greater than one, and the 95% confidence intervals for the IV estimates lie above 1.[21]

Discussion The difference in the short-run and long-run elasticity estimates indicates that the dynamic response of plants' input mixes to relative price changes takes time, even when the shocks are large and permanent. This supports a role for convex adjustment costs. Our results also highlight that quite long time horizons are required to estimate long-run elasticities of substitution when using variation in prices over time, similarly to Boehm et al. (2022).

5.2. Short-Run Elasticity Estimates Using Commodity Prices

In this sub-section, we estimate the elasticity of substitution between material inputs using price changes induced by global commodity price shocks. We estimate these in the same setting, Indian manufacturing, in order to show that our previous larger estimates are not driven by Indian plants reacting more to changes in material input prices than firms in other countries.

For this exercise, we need a relatively long panel with consecutive years of data on plant material input usage. We therefore use the Annual Survey of Industries waves from 1999 to 2013. We use official concordances and panel identifiers to construct a panel at the plant x 1-digit ASICC input level.[22] As before, we construct plant-specific input prices for each 1-digit ASICC input by weighting changes in India's wholesale price

[21] We find similar results if we include 1-digit input fixed effects (Table B.12)

[22] We start the panel in 1999 because we need a long sample period, and the data quality in 1997 and 1998 is poor. See Appendix A1. for more details on the 1999-2013 waves of the ASI and concordances.

Table 3: Short-Run vs. Long-Run Elasticity Estimates

	Short-Run		Long-Run	
	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)
Δln(prices)	0.26	0.31	-0.69	-1.32
	(0.27)	(0.61)	(0.26)	(0.49)
Elasticity	0.74	0.69	1.69	2.32
	[0.21, 1.27]	[-0.51, 1.89]	[1.18, 2.20]	[1.36, 3.28]
First Stage				
Δtariffs		0.12		0.17
		(0.029)		(0.032)
F-stat		16.6		26.9
Observations	3,676	3,676	3,118	3,118
# plants	1,008	1,008	1,334	1,334
# 5-d inputs	272	272	280	280

Notes: This table shows our short-run estimation results from the specifications shown in equations 8 and 9, as well as our long-run estimation results from the specifications in equations 4 and 5. In columns (1)-(2) an observation is a plant $\times$ year $\times$ 1-digit material input category. In columns (3)-(4) an observation is a plant $\times$ 1-digit material input category. The sample for all columns only includes plants that experienced large relative tariff changes in the first year of the liberalization, and excludes any plant-inputs where there were large tariff changes between 1994 and 1996. The dependent variable in columns (1)-(2) are the change in plant spending shares between 1989 and either 1993 or 1994. The dependent variable in columns (3)-(4) 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 at the 1-digit ASICC input level. All regressions include plant fixed effects. Columns (1)-(4) include plant $\times$ year fixed effects. Regressions are weighted by the inverse of the number of inputs used by the plant; each plant is weighted equally. The OLS standard errors are clustered at the 4-digit industry level. We report exposure-robust standard errors from the equivalent tariff-level instrumental variable regressions for the first-stage and IV specifications. For the short-run (long-run) horizon results, the inverse of the Herfindahl index of the exposure weights is 23.3 (23.1), and the largest weight is 0.147 (0.153).

index using Tornqvist expenditure shares (averages between t and $t+h$):

$$\Delta_h \ln(P_{ikt}) = \sum_l \bar{w}^h_{iklt} \Delta_h \ln(P_{klt}) \tag{10}$$

We identify a set of commodities at the HS 6-digit level using the classification from Fally and Sayre (2019). We manually concord these commodities to 5-digit ASICC codes.[23] We construct annual global prices for each commodity as the ratio of global import values and global import quantities reported in the BACI trade database (Fally and Sayre, 2019). We construct the commodity price instrument analogously to the tariff instrument:

$$\Delta_h \ln(P^C_{ikt}) = \sum_l \left(\frac{E^C_{iklt}}{E^m_{ikt}}\right) \Delta_h \ln(P^C_{klt}) \tag{11}$$

We weight ln-changes in the global price of commodity l from t to $t+h$ using period t plant-specific shares of expenditure on commodity l over total material expenditures in input category k. Our specification is analogous to that in Equations 4 and 5:

$$\text{First stage: } \Delta_h \ln(P_{ikt}) = \rho^h_m \, \Delta_h P^C_{ikt} + \lambda^h_{it} + \sum_t \delta_t \left(\frac{E^C_{ikt}}{E^m_{ikt}}\right) + \eta^h_{ikt} \tag{12}$$

$$\text{Second stage: } \Delta_h \ln\left(\frac{E_{ikt}}{E^m_{it}}\right) = \beta^h_m \, \Delta_h \ln(P_{ikt}) + \lambda^h_{it} + \sum_t \delta_t \left(\frac{E^C_{ikt}}{E^m_{ikt}}\right) + \epsilon^h_{ikt} \tag{13}$$

The first main difference is that we now index the changes by the horizon h and pool across years t from 1999 to 2013, We consider 1-year and 2-year horizons. Because the commodity exposure weights do not sum to one, we fall into the 'incomplete shares' case of Borusyak et al. (2022).[24] We, therefore, control for each firm's total share of expenditure on commodities within each 1-digit category $\left(E^C_{ikt}/E^m_{ikt}\right)$. Intuitively, we only exploit the composition of each firm's commodity bundle for identification, not total exposure to commodities. We report exposure-robust standard errors clustered at the 5-digit ASICC level.

The key identification assumption is that fluctuations in relative global prices of commodities are uncorrelated with other determinants of material input demand for manufacturing plants in India. This is plausible given that the main feature of commodities is that they are traded on global markets and we use the average global price as our instrument. Even a comparatively large economy such as India accounted for

[23] Commodities are concentrated in the following 1-digit ASICC categories: '1. Animal and Vegetable Products', '2. Ores and Minerals', '3. Textiles', and '7. Metals'. Averaging from 1999 to 2013, they account for 22% of 5-digit inputs used, 41% of total material expenditures, and 48% of expenditure on imported materials.

[24] To be specific, it isn't necessarily the case that for all i and k $\sum_l E^C_{iklt}/E^m_{ikt} = 1$.

only 2.9% of global commodity imports, averaging across commodities and years from 1999 to 2013.

Table 4: Short-Run Elasticity Estimates with Commodity Price IV

	1-year horizon		2-year horizon	
	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)
Δln(prices)	0.09	0.48	0.04	0.52
	(0.05)	(0.28)	(0.05)	(0.30)
Elasticity	0.91	0.52	0.96	0.48
	[0.81, 1.01]	[-0.03, 1.07]	[0.86, 1.06]	[-0.11, 1.07]
First Stage				
Δtariffs		0.18		0.26
		(0.046)		(0.097)
F-stat		14.6		7.0
Observations	76,982	76,982	42,056	42,056
# plants	18,622	18,622	10,666	10,666
# 5-d inputs	94	94	92	92

Notes: This table shows our short-run estimation results using global commodity price fluctuations as an instrument, from the specifications shown in equations 12 and 13. An observation is a plant $\times$ year $\times$ 1-digit material input category. The sample includes plant in the ASI survey waves from 1999 to 2013. The dependent variable is the log-change in plant spending shares. The dependent variable in the first stage is the change in plant material input price at the 1-digit ASICC input level. All regressions include plant x year fixed effects and controls for plant expenditure share on commodities within each 1-digit ASICC category, interacted with year fixed effects. Regressions are weighted by the inverse of the number of inputs used by the plant; each plant is weighted equally. The OLS standard errors are clustered at the 4-digit industry level. We report exposure-robust standard errors from the equivalent year x 5-digit input level instrumental variable regressions for the first-stage and IV specifications, clustered at the 5-digit ASICC input level. For the 1-year (2-year) horizon results, the inverse of the Herfindahl index of the exposure weights is 81.3 (74.8), and the largest weight is 0.042 (0.038).

We report the estimation results in Table 4. There is a reasonably strong first stage at the 1-year horizon, with the F-statistic equal to 14.6, though this is somewhat weaker at the 2-year horizon. At the 1-year horizon, we estimate that a 10% increase in global commodity prices leads to a 1% increase in domestic Indian input prices over a 1-year horizon. Consistent with typical findings in the literature, the OLS estimate of the elasticity of substitution is below but very close to 1. Our baseline IV estimate is 0.52, with both 0 and 1 in the 95% confidence interval. Extending to the 2-year horizon (columns (3) and (4) of Table 4) and including 1-digit input fixed effects (Table B.13) leads to similar, albeit somewhat noisier, estimates.

Discussion Our estimates of short-run complementarities between material inputs in response to transitory shocks to input prices are consistent with similar estimates in the literature. In particular, Atalay (2017) estimates an elasticity between material inputs very close to 0 using U.S. industry data and military spending shocks for identification. This suggests that our findings of *long-run* substitutability between materials in response to tariff shocks are not due to the particular setting of Indian manufacturing but rather due to the long time horizon and permanency of the price shock.

The previous two empirical results confirm that the likely difference between our estimate and existing ones is that plants in our sample faced a permanent change in relative prices to which they adjusted over an extended period of time. Taken together, this is indicative of manufacturing plants facing sizeable adjustment costs. If it is costly for firms to adjust their production process, they are less likely to do so if they can reasonably expect relative prices to return to baseline within a quarter or a year. The fact that plants' responses to a permanent change takes time to materialize—as we find evidence for in Section 5.1—suggests that these adjustment costs are convex.[25]

6. Other Long-Run Input Elasticities

The tariff changes during India's trade liberalization caused changes in relative prices of material inputs, constituting an ideal setting to estimate the elasticity of substitution between these. However, the trade liberalization also reduced the cost of materials overall compared to other inputs such as energy, services, or capital and labor.

In this section, we estimate a set of other elasticities. First, we use the standard KLEMS classification of nesting and estimate the elasticity between energy, materials, and services, as well as between a capital-labor bundle and an intermediates bundle. Second, we estimate several alternative nesting structures guided by models of firm production used in the literature. We conclude this section by estimating the between-materials elasticity at the industry- rather than the plant level, which accounts for reallocation of production across firms.

6.1. Nested CES Production Function

The first set of elasticities we estimate is the one corresponding to a standard nested CES production function, where the nests follow the KLEMS accounting framework. This production function is commonly used in macroeconomic models due to its tractability in aggregation. The main inputs in this framework are capital (K), labor (L), energy (E),

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

materials (M) and services (S).

6.1.1. Nesting Structure

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.

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

The intermediate input bundle X_{it} itself has a CES structure across 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. M_{it} is in turn given by Equation 2.

6.1.2. Estimation

The empirical specifications for estimating θ^X and ε, as well as the approaches to constructing the tariff instrument and input prices, are analogous to what we describe in Section 4. for the estimation of θ. Similarly, the identifying assumptions remain that the variation in tariffs across 5-digit material inputs is quasi-random. We, therefore, relegate the details to Appendix D and only present the results in the main text.

Table 5 presents the estimates of θ^X and ε. The first stages are reasonably strong, with F-statistics of 18 and 16. The IV point estimates (standard errors) of θ^X and ε are less than one; 0.66 (0.33) and 0.79 (0.36), respectively. The 95% confidence intervals include Cobb-Douglas for both elasticities. We can reject Leontief for the elasticity of substitution between energy, materials, and services inputs, but not for the elasticity between value-added and intermediates. We find similar results for a number of robustness checks, which we report in Tables B.14 and B.15.

These estimates, therefore, suggest that inputs are less substitutable at higher levels of aggregation. While we find high elasticities between different material inputs, it seems that materials, energy, and services, as well as intermediate inputs and value-added, are not very substitutable even in the longer run.

Table 5: Upper CES Nest Elasticity Estimates

	θ^X		ε	
	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)
Δln(prices)	0.53	0.37	0.56	0.21
	(0.20)	(0.29)	(0.17)	(0.45)
Elasticity	0.47	0.63	0.45	0.79
	[0.08, 0.86]	[0.06, 1.20]	[0.11, 0.77]	[-0.09,1.67]
First Stage				
Δtariffs		0.16		0.13
		(0.037)		(0.032)
F-stat		17.8		15.6
Observations	13,330	13,330	6,671	6,671
# plants	6,813	6,813	6,671	6,671
# 5-d inputs	309	309	309	309

Notes: This table shows our estimation results from the specifications shown in equations 21 and 22 (columns (1) and (2), and 23 and 24 (columns (3) and (4)). An observation in column (1) and (2) is a plant x input (energy or services). An observation in columns (3) and (4) is a plant. The dependent variable in the OLS and IV specifications in columns (1) and (2) are the change in plant relative spending shares on materials vs. energy or materials vs. services between 1989 and 1996. The dependent variable in the OLS and IV specifications in columns (3) and (4) are the change in plant relative spending shares on intermediates vs. capital and labor between 1989 and 1996. The dependent variable in the first stage is the change in relative input prices at the 1-digit ASICC input level. Regressions are weighted by the inverse of the number of inputs used by the plant; each plant is weighted equally. The OLS standard errors are clustered at the 4-digit industry level. We report exposure-robust standard errors from the equivalent tariff-level instrumental variable regressions for the first-stage and IV specifications. For the θ^X (ε) results, the inverse of the Herfindahl index of the exposure weights is 47.6 (47.5), and the largest weight is 0.084 (0.084).

6.2. Alternative Nesting Structures

The nesting structure we estimated in the previous sub-section is commonly used, yet only one of many possible nesting structures. In what follows, we consider alternative nesting structures that have also been considered in the literature for which our setting allows us to estimate the relevant elasticities. We briefly discuss these below; Table B.16 contains all estimation results.

Alternative levels of aggregation of materials Our baseline results estimate the elasticity of substitution across 8 categories of materials, as classified by the ASI. Alternatively, we can estimate the same elasticity across more disaggregated categories. We follow the level of aggregation used in Atalay (2017), which corresponds to a combination of 2-digit and 3-digit NAICS codes. The elasticity across these finer 14 material input categories is very similar at 2.5.

Materials vs. Labor and/or Capital Following the KLEMS classification, our baseline nesting structure imposes a constant elasticity between a bundle of capital and labor and a bundle of materials, energy, and services. Alternatively, one can imagine that firms first combine labor and materials, such as typically considered in the literature on outsourcing (Chan, 2023; Oberfield and Boehm, 2022), or materials and a capital-labor bundle (Oberfield and Raval, 2021; Castro-Vincenzi and Kleinman, 2024).

We estimate the elasticity between labor and materials as well as between a capital-labor bundle and materials.[26] For both these elasticities, we estimate gross complementarities. The point estimates for the materials-labor elasticity are 0.76 (OLS) and 1.04 (IV). The elasticity between materials and value-added is even lower than between labor and materials, with point estimates of 0.33 (OLS) and 0.28 (IV).

Materials vs Energy / Services Our baseline nesting structure imposes a common elasticity between energy, materials, and services. Alternatively, we could estimate the elasticity separately between materials and energy or materials and services.[27] The importance of the substitutability of energy in production has been highlighted in recent years, given the hike in energy prices in Europe following Russia's invasion of Ukraine. We estimate gross complementarities between energy and materials using OLS regressions, but very close to Cobb-Douglas with the IV. The point estimates are 0.41 (OLS) and 1.00 (IV), with the latter statistically different from 0 but not from 1. Interestingly,

[26]For completeness, we also estimate an elasticity between materials and capital. The specifications are analogous to those described in Section 4. and Appendix D.

[27]Since we only have an instrument for materials prices, we cannot estimate the elasticity between energy and services.

our point estimates suggest that energy and materials are more substitutable than services and materials.

6.3. Plants vs. industries

The plant-level elasticities in Table 1 and 5 are the key structural parameters for the macroeconomic model we present in Section 7.. However, the macroeconomics and trade literature have mostly used models with industry production functions - i.e., without an explicit nesting of plants within each industry. In these models, the *industry*-level elasticities of substitution are the key structural—constant—parameters.[28]

The key difference between plant and industry elasticities of substitution is that the latter captures 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. As a result, 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.

To speak to this literature, we estimate the industry-level elasticity of substitution between 1-digit materials. The specifications are identical to the plant-level specifications in Equations (4)-(5), 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.[29]

The estimation results are presented in the last column of Table B.16. We estimate an elasticity of 3.3 between different categories of materials. However, the industry estimates are less precise than the plant estimates, and the difference is not statistically significant. The higher industry elasticity than plant elasticity suggests that *total* inputs are being reallocated towards plants that experienced greater decreases in tariffs. This is consistent with the elasticity of demand facing firms being greater than our estimated elasticity of substitution between materials (Oberfield and Raval, 2021).

[28] Caliendo and Parro (2015) and Caliendo, Parro and Tsyvinski (Forthcoming) are recent examples.

[29] 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. One difference relative to the plant-level specification is that we do not drop industries with positive imports, as this would dramatically reduce the sample size.

7. The Aggregate Importance of Intermediate Input Substitutability

The fact that we estimate a high degree of substitutability between materials in the long run has two important consequences. On the one hand, the economy is more resilient to negative productivity shocks than previously thought. On the other hand, distortions, such as those arising from market power, contracting frictions, or direct government policy, are even more harmful than previous estimates suggest. This is particularly true if such frictions apply directly to intermediate inputs.

To quantify this, we embed the model of plant-level production from sections 2. and 6. into a general equilibrium framework calibrated to the Indian economy. We briefly outline the model and calibration strategy below and relegate details to Appendix E. We use the model to run a set of counterfactuals using three possible values for the elasticity of substitution between materials: the substitutes case (our estimated $\theta = 2.5$), the standard Cobb-Douglas case ($\theta = 1$), and a complements case ($\theta = 0.1$), and compare the predicted effects on aggregate output.

We directly use the estimated long-run elasticity and do not take a stand on the exact mechanism by which substitution is higher in the long run than in the short run. Our quantitative model is thus a reduced form for a variety of such mechanisms that have been proposed by the literature, such as adjustment costs (Boehm et al. (2022)), putty-clay production (Gilchrist and Williams (2000)), or the fact that it may take time to find new suppliers (Huneeus (2018)).

7.1. Model and Calibration

For the sake of maximum transparency, we choose a standard model of a static, small open economy with multiple sectors, building on Long and Plosser (1983). In each sector, there is a large, exogenous number of perfectly competitive firms that use labor and intermediate inputs in production. Each intermediate input has a domestic and an imported variety; otherwise inputs are aggregated as in sections 2. and 6..[30] Firm output is aggregated to a sectoral good using a standard CES aggregator. The sectoral good is used as intermediate input or further aggregated to a single consumption good, which is used domestically and exported to pay for imported inputs.

We calibrate the model to sectoral input-output shares from the World Input-Output Database (WIOD) as well as plant-level moments—such as the distribution of firm-level productivity and technologies—from the ASI. We calibrate the model to 1996, which is the earliest year for which both the WIOD and the ASI are available. We use our esti-

[30]Our baseline estimation in Section 4. uses only plants that do not use imported intermediates. In the model, these would be plants with a zero weight on the imported variety in that new lower nest.

mates from this paper for the elasticities of substitution between materials, energy, and services as well as between value-added and intermediates.[31] The corresponding cross-sector elasticities on the consumption side are set to 2.6, as estimated by Hobijn and Nechio (2019). That is, goods from different sectors are substitutes in consumption, irrespective of the calibration on the input side.

7.2. Resilience to TFP shocks

What happens to the economy when a sector suffers a negative TFP shock? Typically, the multi-sector models used to explore such questions share a similar underlying structure to the one in this paper, albeit focusing on transitory shocks and a short time horizon.[32] With most of the literature pointing to short-run complementarities in production, a low value of the elasticity of substitution is generally used. This, in turn, results in relatively larger aggregate impacts of negative sectoral shocks.

In contrast, our findings suggest that in response to a permanent TFP shock over the long run, an economy would be able to adjust and dampen some of these negative effects. For example, in the complements calibration, a 50% productivity shock to one sector of the Indian economy would, on average, lead to a more than 60% reduction in output from that sector, as well as a 3.7% decline in aggregate output. Using the elasticities we estimate, the same sectoral productivity shock would, on average, lead to only a 2.9% drop in aggregate output. In a more substitutable economy, the affected sector contracts by more—82% on average—, dampening the resulting fall in aggregate output.

7.3. Input Distortions

The flip side of the economy's increased flexibility in dampening negative TFP shocks is that distortions and taxes can have more detrimental effects. Such distortions are likely to be ubiquitous, especially in developing countries. Examples include contracting frictions (Boehm, 2022; Oberfield and Boehm, 2020), transportation cost (Peter and Ruane, 2022), or different prices charged by input suppliers (Burstein et al., 2024).

To gauge how big such distortions may be in our context, we use the detailed plant-level data from the ASI. Even within industries, there is significant heterogeneity in input spending shares across plants. In the baseline model, we assumed that all heterogeneity

[31] We use our baseline estimate of $\theta = 2.5$ also for the elasticity of substitution between energy inputs and between services inputs. The conclusions of the following section are not sensitive to this assumption as we get similar results when setting these two elasticities to 1.

[32] Many studies have applied the framework of Baqaee and Farhi (2019) and Baqaee and Farhi (2024) to various countries and settings. For example, Bachmann et al. (2022) estimate the effect of a German embargo on Russian gas imports.

in plant spending shares is a result of different technologies used. If, instead, one were to interpret heterogeneity in spending shares as resulting from distortions, their implied log standard deviation equals 1.46.

Starting from our undistorted initial calibration, we consider a counterfactual in which we introduce firm-level distortions to material inputs with variance equal to 1/3 of the observed dispersion in the data.[33] We choose 1/3 so as to not overstate the degree of input distortions, since some of the observed heterogeneity is likely due to differences in technology or measurement error (Bils et al., 2021).

Table 6 reports the results. When material inputs are substitutes, distorting input choices leads to a 28% drop in GDP. In contrast, in an economy where material inputs are complements, the same level of, say, contracting frictions with suppliers would only cost around 8% of output. The fact that losses are over 4 times higher in the longer run is due to the economy's greater flexibility: the more firms adjust their input choices in response to the frictions, the more they distort production allocations relative to the first best.

Table 6: GDP losses from input distortions

Substitutes	Cobb-Douglas	Complements
-27.7%	-13.7%	- 7.9%

Notes: The table shows the change in aggregate GDP from adding firm-level distortions to material inputs. The distortions are drawn from a log-normal distribution with mean zero and a standard deviation of 0.5. Each column corresponds to a different calibration of the elasticity of substitution between materials, θ.

7.4. Sectoral Subsidies

The input distortions we considered above generate inefficient dispersion in input use across firms but do not directly favor one sector over another. However, many governments around the world have adopted industrial policies favoring particular sectors (Liu, 2019), often targeting upstream sectors producing intermediate inputs (Lane, 2025). While there may be various reasons in favor of industrial policies, such as offsetting existing distortions, they also have the potential to cause significant welfare losses if badly targeted.

To illustrate this point, we simulate two sets of counterfactuals. First, we consider a permanent uniform 30% revenue subsidy to all firms in a sector.[34] If material inputs are complements, this policy would lead to a 1.5% drop in aggregate output on average (Table 7). With our estimated elasticities, the drop in GDP is 2.5%—67% larger.

[33]The distortions are drawn from a lognormal distribution with mean zero.

[34]All policies we consider are paid for by a lump-sum tax to the household.

Second, we consider a policy subsidizing purchases of domestic intermediate goods or services from a sector. This would be a prime example of import substitution.[35]

We implement the policy as a subsidy paid to all firms in proportion to their input use. In an economy in which material inputs are complements, this policy causes less of a decline in aggregate TFP than subsidizing the entire sector's output. As the subsidy only affects intermediates and not consumption—where goods are substitutes—sectoral subsidies cause less distortion overall. However, when intermediates are substitutes, subsidizing inputs from one sector has much larger distortionary effects on firms' production choices. As firms tilt their intermediates bundle more towards the subsidized input, this sector's share of the aggregate intermediate good increases by 2% on average, compared to 0.8% when materials are complements. As a result of the distortion between consumption and intermediate use of the subsidized sector, aggregate losses are large, amounting to over 4% of GDP on average.

Table 7: GDP losses from a 30% sectoral subsidy

	Substitutes	Cobb-Douglas	Complements
Subsidy to one sector's output	-2.5%	-1.8%	-1.5%
Subsidy to inputs from one sector	-4.4%	-1.7%	-0.8%

Notes: Table 7 shows the average change in aggregate GDP from subsidizing one of the economy's sectors by 30%. The first row corresponds to a uniform output subsidy to all firms in a given sector. The second row corresponds to a subsidy to inputs used from a given sector.

7.5. Trade Liberalization

Last, we use the quantitative model to assess the gains from India's trade liberalization. Since the WIOD does not go back to 1989, we first use the model to generate calibration targets. That is, we feed the tariff *increases* from 1996 to 1989 into the model with our estimated elasticity and use the resulting pre-liberalization equilibrium as calibration targets for all three versions of the model for 1989.

Starting from the constructed 1989 baseline, we then simulate the observed decline in tariffs from 1989 to 1996 and compare the pre- and post-liberalization equilibria in the three calibrations. Since we model India as a small open economy, the tariff changes have no effect on world prices, and there is full pass-through to the price of imported goods.

Table 8 shows the results. If intermediate inputs were complements, GDP would have increased by just below 3.2% as a result of the observed tariff declines. With our

[35]That said, we have also run counterfactuals in which all inputs from a certain sector, domestic or imported, are subsidized and find similar aggregate effects.

estimated elasticity, that number is 5% larger. The reason this particular counterfactual is less sensitive to the elasticity of substitution between intermediate inputs is that the trade liberalization acts in a manner akin to a sectoral productivity shock. Tariffs declined, on average, by about 30%. Coupled with an average import share of intermediates of less than 15% in 1989, the trade liberalization constitutes a shock that is small enough for Hulten's theorem to hold approximately.

Table 8: Gains from the Trade Liberalization

	Substitutes	Cobb-Douglas	Complements
Change in GDP	3.3%	3.2%	3.2%

Notes: Table 8 shows the effects on aggregate output of the tariff declines during India's trade liberalization. The pre-liberalization equilibrium is constructed by feeding the tariff changes from 1996 to 1989 into the 1996 model with $\theta = 2.5$. All three models are then calibrated to the model-implied 1989 equilibrium, and the same tariff decline from 1989 to 1996 is then simulated to obtain the GDP response.

8. 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 2.5 – a significant departure from existing short-run estimates which are close to 0.

We argue that the elasticity of substitution is sensitive both to the time horizon it is estimated over and to the nature of the shock. We find evidence that it takes plants time to adjust to the permanent price change over the trade liberalization—elasticities are lower over four instead of seven years. Further, intermediate inputs appear to be complements when estimated in response to temporary shocks such as those induced by commodity price fluctuations.

The value of the elasticity of substitution between intermediate inputs is crucial for a range of questions in macroeconomics. Most prominently, we find that permanent distortions to intermediate inputs, such as those caused by a poor contracting environment, may lead to aggregate losses on the order of 30%—3.5 times larger than in the short run when intermediates are complements.

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Appendix
For Online Publication

A Annual Survey of Industries

A1. Details of ASI Surveys

ASI Coverage and Sampling. The ASI is a nationally representative, yearly survey of registered Indian manufacturing plants. Each survey wave covers accounting years (e.g., 1989-1990); for brevity, we refer to it by the earlier of the two years (e.g., 1989). From 1989 to 1996 the survey covers 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.[36] The automatic size threshold for inclusion in the Census scheme increased to 200 workers in 1997 and 1998 before falling back to 100 workers from 1999 onward. Table A.1 provides additional details on how the methodology used to determine the ASI survey sample changed from 1987 to 2013. 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)).

Measurement of material expenditures. The data from ASI surveys are provided in two forms: 'summary' releases and 'detailed' releases. While the summary releases contain only commonly available plant-level variables such as sales, employment, and total materials expenditures, the detailed releases of the ASI contain information on values and quantities of each intermediate input and product. These detailed releases are available in 1989, 1993, 1994, and from 1996 on.[37]

In 1989, 1993, and 1994, the classification used to categorize material inputs was the ASI Item Code classification. The input codes used in the classification were an 8-digit combination of the plant's 4-digit industry and a 4-digit industry-specific item code. From 1996 on, the ASICC classification was adopted, which classified inputs using 5-digit codes. We report the main 3-digit and 5-digit inputs within each 1-digit ASICC

[36] 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 four plants and plants belonging to a state $\times$ 3-digit industry group with fewer than 20 plants.

[37] Summary datasets are available for 1985-1988 and 1990-1992. No ASI release was made publicly available for 1995.

category in Table A.2. No official concordance is available from the ASI Item Code classification to the ASICC classification, and we therefore constructed our own through a combination of text matching and manual checks, and manual concordances. When a corresponding 5-digit ASICC code was not available, we matched to the nearest 3-digit ASICC code. In total, we concord 6,645 unique item code descriptions to 2,784 5-digit ASICC codes and 224 3-digit ASICC codes. Table A.3 provides examples of the concordance. The ASICC classification underwent further revisions throughout the 2000s and changed to the NPCMS 7-digit classification in 2010. We link these together using official concordances.

Between 1989 and 1996 there was no limit on the number of inputs plants were required to report. From 1997 on, plants were only required to report their top 5 most used inputs, with many expenditures being classified in the 'Other' category. As a result, the median number of 5-digit inputs reported by plants fell from 6 in 1996 to 3 in 1997, with the 90th percentile falling from 13 to 5. For plants that we observe in both 1996 and 1997, the decline is even larger, from a median of 7 inputs to 3 inputs reported. Another measurement issue with the ASI surveys between 1998 and 2000 is that the share of inputs classified as 'Other basic items' rose dramatically. From a negligible share in 1996 and 1997, this share rose to 62% in 1998, before falling gradually; 39% in 1999, 34% in 2000, 7% in 2001, and under 1% from 2002 on. For this reason, we drop the 1998 survey for the short-run elasticity estimation using commodity prices in section 5.2..

A2. Construction of Plant-Specific Input Prices and Tariffs

Concordances of Tariffs and WPI to HS6 level. India's Wholesale Price Index contains price information for almost 450 products. We construct a manual concordance between the WPI product categories and 617 unique ASICC 5-digit codes. Table A.4 reports examples from the concordance. Data on import tariffs from Topalova (2010) are at the level of HS6, of which there are 5,140 categories. We construct a manual concordance between the 617 5-digit ASICC codes for which we observe prices to 649 HS6 categories. We keep only inputs for which both prices and tariffs are available from 1989 to 1997. In addition, we drop a set of goods (mostly cereal grains, oil seeds, and derived agricultural products) where imports and exports were restricted to the public sector (canalization). Our resulting price and tariff dataset covers 495 5-digit ASICC categories.

Construction of prices and tariff variables. We construct plant-specific changes in 1-digit tariffs as the weighted average change in tariffs on the 5-digit material inputs used by plant i, as per equation 11 in the main text. Without loss of generality, we can rewrite

Table A.1: Sampling Methodology for Indian ASI

Period	Census Sector	Sample Sector
1987–1996	12 less industrially developed states, 100 or more workers, all joint returns, all plants within state $\times$ 4-digit industry if $<$ 4 plants, all plants within state $\times$ 3-digit industry if $<$ 20 plants	Stratified within state $\times$ 3-digit industry (NIC-87), minimum sample of 20 plants within strata, otherwise 1/3 of plants sampled
1997	12 less industrially developed states, plants with $>$ 200 workers, 'significant units' with $<$ 200 workers but contributed highly to value of output between 1993–1995, public sector undertakings	Stratified within state $\times$ 3-digit industry (NIC-87), minimum of 4 plants sampled per stratum
1998	Complete enumeration states, plants with $>$ 200 workers, all joint returns	Stratified within state $\times$ 4-digit industry (NIC-98), minimum of 8 plants per stratum
1999–2003	Complete enumeration states, plants with $\geq$ 100 or more workers, all joint returns	Stratified within state $\times$ 4-digit industry (NIC-98), minimum of 8 plants per stratum
2004–2006	6 less industrially developed states, 100 or more workers, all joint returns, all plants within state $\times$ 4-digit industry with $<$ 4 units	Stratified within state $\times$ 4-digit industry, 20% sampling, minimum of 4 plants
2007	5 less industrially developed states, 100 or more workers, all joint returns, all plants within state $\times$ 4-digit industry with $<$ 6 units	Stratified within state $\times$ 4-digit industry, minimum 6 plants, 12% sampling fraction: exceptions
2008–2013	6 less industrially developed states, 100 or more employees, all joint returns, all plants within state $\times$ 4-digit industry with $<$ 4 units	Stratified within district $\times$ 4-digit industry, minimum 4 plants, 20% sampling fraction

Notes: information regarding sampling methodology for each ASI wave is available in the metadata files here: http://microdata.gov.in/nada43/index.php/catalog/ASI/about.

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.

Table A.3: 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.4: 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.

the expression for how we construct tariffs in equation 11 as:

$$\Delta\tau_{ik} = \sum_{m\in 3-digit} w_{ikm}^{1989}\,\Delta\tau_{ikm} \tag{14}$$

where

$$\Delta\tau_{ikm} \equiv \sum_{n\in 5-digit} w_{ikmn}^{1989}\,\Delta\tau_{kmn} \tag{15}$$

and w_{ikm}^{1989} is the 1989 expenditure share of plant i on 3-digit material input m within 1-digit material category k, and w_{ikmn}^{1989} is the 1989 expenditure share of plant i on 5-digit material input n within 3-digit material category m.

It is useful to decompose $\Delta\tau_{ik}$ in this way because there are some cases in which we cannot construct $\Delta\tau_{ikm}$. This can be because w_{ikmn}^{1989} is missing as a result of the incomplete concordance between the ASI Item Code classification and ASICC classification at the 5-digit level. It can also be because $\Delta\tau_{kmn}$ is missing due to an incomplete concordance between the HS6 classification and the 5-digit ASICC classification.

If we observe that firm i has positive expenditures on 3-digit material category m but we cannot construct $\Delta\tau_{ikm}$ for the above reasons, we replace it in equation 14 with an *aggregate* tariff for that 3-digit material input category, $\Delta\tau_{km}$, which we construct analogously to equation 16 but using aggregate 1989 expenditure shares from the ASI:

$$\Delta\tau_{km} \equiv \sum_{n\in 5-digit} w_{kmn}^{1989}\,\Delta\tau_{kmn} \tag{16}$$

We follow an analogous approach for constructing $\Delta\text{ln}(P_{ik})$. The only difference is that we use *average* expenditure shares between 1989 and 1996 as weights instead of 1989 shares. The reason for this is that the resulting Tornqvist price index $\Delta\text{ln}(P_{ik})$ is a second-order approximation to the change in the true price index for any constant elasticity production function between 3-digit and 5-digit inputs. For robustness, we also show our results using a Laspeyres price index, which uses 1989 expenditure shares as weights (Table B.9).

We follow this approach in order to increase the sample of plants included in the estimation in light of the measurement challenges resulting from incomplete concordances. It does not affect the identification assumptions, which remain as described in section 4., and the exposure-robust standard errors from Borusyak et al. (2022) remain correct.

A3. Comparison of ASI Imports to Customs Data

In order to validate the measure of imports in the ASI, we compare aggregate imports at the 1-digit ASICC level to imports reported from UN Comtrade. We construct a concordance from the 2-digit HS codes in the trade data to the 1-digit ASICC codes. For each 1-digit ASICC code, we report in Table A.5 the ratio of ASI imports to aggregate imports from Comtrade both for 1989 and 1996.[38]

Table A.5: Share of ASI Imports Relative to Customs Data

	1989	1996
1. Animal, Vegetable, Horticulture, Forestry Products, Beverages, etc.	9.6	15.6
2. Ores, Minerals, Mineral fuels, Lubricants, Gas & Electricity	37.3	89.4
3. Chemical and Allied products	43.9	71.9
4. Rubber, Plastic, Leather & products thereof.	48.2	55.8
5. Wood, Cork, Thermocol & Paper and articles thereof.	29.8	46.7
6. Textile and Textile Articles.	30.8	62.2
7. Base metals, Products thereof & Machinery equipment and parts thereof	30.7	55.2

Notes: For each year and 1-digit ASICC product category, the table reports 100 x the ratio of total imports in the ASI to total imports from UN Comtrade. The classifications are made consistent using a concordance of 2-digit HS codes to 1-digit ASICC codes.

There are two main reasons that reported imports in the ASI should understate Comtrade imports. Firstly, the official trade data includes imports of both final goods and intermediate inputs. For example, for the Textiles input category, Comtrade imports will include both intermediate materials (such as linen or foreign cloth) and finished clothes for wholesale and retail. Secondly, Comtrade does not include information on which sector is doing the importing. It therefore includes imports not only by manufacturing firms but also by firms in the construction, mining, or service sectors.

Indeed, Table A.5 shows that, for both 1989 and 1996, the ratio of ASI imports to Comtrade imports is less than 100%. On average the share is 57% in 1996 and 33% in 1989.[39] Notably, there is a lot of heterogeneity across input categories in ways we would expect ex-ante. In particular, we see the lowest ratio for '1. Animal, Vegetable, Horticultural, [...]' (15.6% in 1996), which we expect to be mostly food imports for household consumption goods rather than intermediate inputs for firms. Conversely, the highest ratios are for '2. Ores, Minerals, [...]' and '3. Chemical and Allied Products, at 71.9% and

[38] We omit fuel imports from Comtrade data as these are reported separately in the ASI. We also omit any HS product category with machinery in the title, as these are more likely to be capital goods than materials.

[39] The lower share in 1989 is likely the result of our reliance on a concordance from the ASI Item Code classification to the ASICC classification.

89.4% respectively, which we would expect to be mostly intermediate inputs in manufacturing.

B 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. These requirements meant that registered manufacturing plants were required to obtain government approval whenever they wanted to open a new factory, significantly expand production, create a new product, or change location. They 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.[40] 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 5 and bias our IV estimate β_m.

To address 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 Aghion, Burgess, Redding and Zilibotti (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.[41] 51 out of 112 industries were delicensed in 1991, and 63 industries underwent FDI reform.

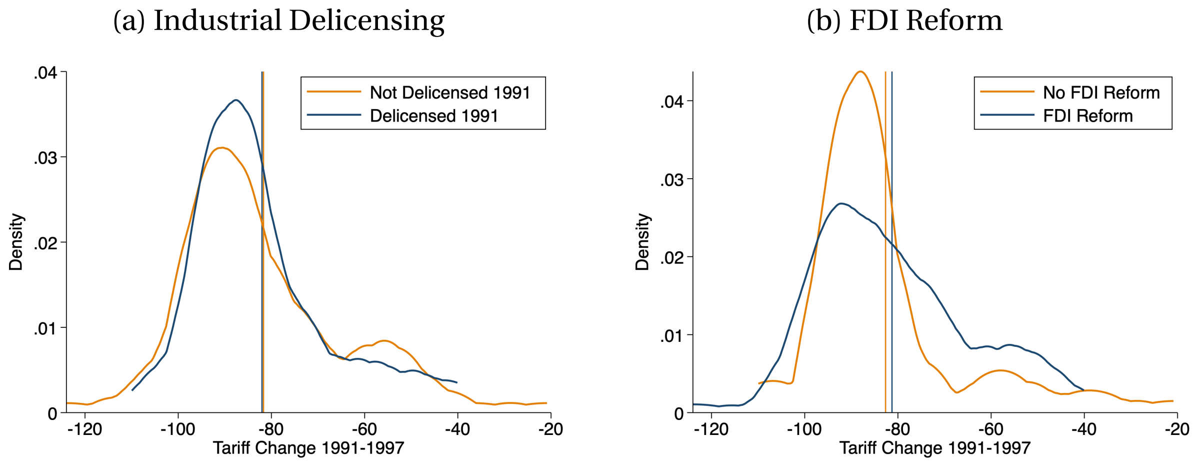
The mean 1991-1997 tariff change for industries delicensed in 1991 was -82.0%, compared to -81.7% for industries which weren't delicensed. The mean 1991-1997 tariff change for industries with FDI reform in 1991 was -81.3%, compared to -82.6% for industries without FDI reform. Neither of the differences are statistically significant.[42] To dig deeper, in Figure A.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.

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

[41] 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.

[42] 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 1991 was -77.7%, compared to -80.7% for industries without FDI reform.

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



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 that 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 was some opening up to FDI in 1991 and industries 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).

not, and for industries that 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 that 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 experiencing other reforms, these results reassure us that these other reforms are unlikely to be biasing our empirical elasticity estimates.

C Quality Bias

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 k and k'. Denote P_{ik} and $P_{ik'}$ the measured input prices for plant i, and κ_{ik} and $\kappa_{ik'}$ the unobserved quality term. True quality-adjusted prices $\tilde{P}$ are therefore:

$$\tilde{P}_{ik} = \frac{P_{ik}}{\kappa_{ik}} \tag{17}$$

The econometrician estimates the following two-stage least squares specification:

$$\text{First stage: } \Delta\ln\left(\frac{P_{ik}}{P_{ik'}}\right) = \rho\left(\Delta\tau_{ik} - \Delta\tau_{ik'}\right) + \eta_i \tag{18}$$

$$\text{Second stage: } \Delta\ln\left(\frac{E_i^k}{E_i^{k'}}\right) = \beta_m \Delta\ln\left(\frac{P_{ik}}{P_{ik'}}\right) + \epsilon_i \tag{19}$$

Assuming that the only potential source of bias is quality changes κ, the IV estimate of θ is then given by:

$$\hat{\theta}^{IV} = \theta - (\theta - 1)\frac{\text{Cov}[\Delta\ln\left(\frac{\kappa_{ik}}{\kappa_{ik'}}\right), (\Delta\tau_{ik} - \Delta\tau_{ik'})]}{\text{Cov}[\Delta\ln\left(\frac{P_{ik}}{P_{ik'}}\right), (\Delta\tau_{ik} - \Delta\tau_{ik'})]} \tag{20}$$

The bias term depends on the covariance between *unmeasured* relative quality changes and tariff changes, divided by the covariance between *measured* relative price changes and tariff changes. If tariff changes do not systematically affect unmeasured quality, then the bias is 0. However, if tariff reductions induce quality upgrading, then the IV estimate of θ is upward biased, provided that θ is greater than one. 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 $\Delta\ln\tilde{P}_k = \Delta\ln P_k + \mathrm{x} \cdot \Delta\tau_k$, 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 15.6% (see Table 1). This magnitude of a quality bias would imply that the true elasticity of substitution θ is 2.29, as opposed to the 2.42 which we report in Table 1. A quality response to tariffs 50% as large as the observed price response to tariffs would imply that the true elasticity of substitution is 1.95. 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 1.71.

D Details of Estimation of θ^X and ε

This appendix shows the empirical specifications for the estimation of θ^X and ε in section 6.1. and provides details on how we construct the main variables in the estimation.

D1. Empirical Specifications

We estimate θ^X using the following two-stage least squares specification:

$$\text{First stage: } \Delta\ln\left(\frac{P_i^m}{P_i^z}\right) = \rho_x\,\Delta\tau_i + \sum_{z\in\{e,s\}}\lambda_z + \eta_i^z \tag{21}$$

$$\text{Second stage: } \Delta\ln\left(\frac{E_i^m}{E_i^z}\right) = \beta_x\,\Delta\ln\left(\frac{P_i^m}{P_i^z}\right) + \sum_{z\in\{e,s\}}\lambda_z + \epsilon_i^z \tag{22}$$

where i denotes a plant, m denotes materials, while z denotes energy e or services s. We look at long differences Δ between 1989 and 1996. E_i^m/E_i^z are expenditures by plant i on materials relative to expenditures on energy or services. $\Delta\ln\left(P_i^m/P_i^z\right)$ is the change in plant i's price for materials vs. energy or services. $\Delta\tau_i$ is the average change in tariffs on plant i's material inputs. λ_z is a constant that absorbs aggregate trends in relative expenditures or prices for materials relative to energy or services.

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

$$\text{First stage: } \Delta\ln\left(\frac{P_i^x}{P_i^v}\right) = \rho_v\,\Delta\tau_i + \lambda_v + \eta_i^v \tag{23}$$

$$\text{Second stage: } \Delta\ln\left(\frac{E_i^x}{E_i^v}\right) = \beta_v\,\Delta\ln\left(\frac{P_i^x}{P_i^v}\right) + \lambda_v + \epsilon_i^v \tag{24}$$

As before, i denotes a plant, and we look at long differences Δ between 1989 and 1996. E_i^x/E_i^v is the expenditure share on intermediates relative to capital and labor. $\Delta\ln\left(\frac{P_i^x}{P_i^v}\right)$ is the change in plant i's price of intermediates relative to the price of capital and labor. $\Delta\tau_i$ is the average change in tariffs on plant i's material inputs. λ_v is a constant that absorbs any aggregate trends in relative expenditures or prices for intermediates relative to capital and labor.

D2. Variable Construction

Input Prices

We construct $\Delta\ln P_i^m$ analogously to $\Delta\ln P_{ik}$ in Equation 10. We aggregate across 5-

digit ASICC material input categories l using average plant expenditure shares:

$$\Delta\ln(P_i^m) = \sum_l \bar{w}_{il}\Delta\ln(P_l) \tag{25}$$

The weights are expenditure shares averaged between 1989 and 1996: $\bar{w}_{il} = (w_{il}^{1989} + w_{il}^{1996})/2$. The resulting Tornqvist price index $\Delta\ln(P_i^m)$ is a second-order approximation to the change in the true price index for any constant elasticity production function between 5-digit inputs and is therefore consistent with our estimates from Section 4..

Similarly, we construct Tornqvist price indices for energy and services:

$$\Delta\ln(P_i^z) = \sum_l \bar{w}_{il}^z\Delta\ln(P_l^z) \tag{26}$$

We use price data for energy (P_l^s) and services (P_l^s) from World KLEMS for the following disaggregated inputs: 'Coke, Refined Petroleum Products and Nuclear fuel', 'Electricity, Gas and Water Supply', 'Transport and Storage', 'Post and Telecommunication', 'Financial Services' and 'Business Service'. We construct the weights $\bar{w}_{il}^z$ using data on plant expenditures for similarly disaggregated energy and services inputs available in the ASI.

We construct the change in plant i's intermediate input price index $\Delta\ln P_i^x$ as the expenditure-weighted average of $\Delta\ln P_i^e$, $\Delta\ln P_i^m$ and $\Delta\ln P_i^s$:

$$\Delta\ln(P_i^x) = \bar{w}_{il}^e\Delta\ln(P_i^e) + \bar{w}_{il}^m\Delta\ln(P_i^m) + \bar{w}_{il}^s\Delta\ln(P_i^s) \tag{27}$$

The weights sum to one and are plant expenditure shares on energy, materials, and services averaged between 1989 and 1996.

Finally, we use a capital deflator and an industrial worker CPI deflator from the Reserve Bank of India (RBI) to construct the Tornqvist price index for the capital-labor bundle, P_i^v:

$$\Delta\ln(P_i^v) = \bar{w}_{il}^k\Delta\ln(P_i^K) + \bar{w}_{il}^l\Delta\ln(P_i^{CPI}) \tag{28}$$

We construct the weights as the plant's average capital and labor cost share, respectively (which sum to one). Labor costs are reported in the data. We construct expenditures on capital as RK_i where K_i is the reported book value of the capital stock, and R is the assumed rental rate. We set this equal to 20%.

Tariffs We construct the tariff instrument using the same approach as for input prices:

$$\Delta\tau_i = \sum_l w_{il}^{1989}\Delta\tau_l \tag{29}$$

The main difference is that we weight tariff changes using 1989 material expenditure shares rather than average shares between 1989 and 1996.

Estimation Sample The estimation samples consist of plants that we observe in the ASI in both 1989 and 1996. We trim the 1% tails of spending share changes, price changes, and tariff changes.[43] Table A.1 reports summary statistics for the estimation samples.

Table A.1: 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.

[43] We find similar results when trimming 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.

E Model Appendix

We lay out the model and calibration underlying all results in Section 7. and describe the counterfactuals.

E1. Setup

Heterogenous Firms The economy consists of J sectors, which are classified into three 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 Sections 2. and 6.1. 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:

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

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

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

ε, θ^X, and θ are the respective elasticities of substitution for each input bundle.[44] 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).[45]

Firms are perfectly competitive; they take input and output prices P_{ji} as given when

[44] 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.

[45] 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.

maximizing profits Π_{ji}.

$$\Pi_{ji} = \max \ (1-\tau_{ji})P_{ji}Q_{ji} - wL_{ji} - \sum_{\{z,k\}} P^D_{z,k} Z^D_{jik} - \sum_{\{z,k\}} P^I_{z,k} Z^I_{jik}$$

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.

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 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:

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

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

$$Z^c_k = \left[\delta^z_{c,k} (Z^{c,D}_k)^{\frac{\eta_c-1}{\eta_c}} + (1-\delta^z_{c,k})(Z^{c,I}_k)^{\frac{\eta_c-1}{\eta_c}} \right]^{\frac{\eta_c}{\eta_c-1}}$$

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 $\sum_{k=1}^{J^z} \omega^z_k = 1$. The final good producer minimizes costs, taking domestic input prices ($P^D_{z,k}$) and imported input prices ($P^I_{z,k}$) as given.

The aggregate consumption good is the numéraire in the economy with a price normalized to 1. It is used for consumption and exported to pay for imports.

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. With perfect competition, the only source of income is labor income.[46]

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 $\{\varepsilon, \theta^X, \theta, \eta, \{\gamma_{ji}\}, \{\pi_{ji}^z\}, \{\pi_{jik}^z\}, \{\delta_{jk}^z\}\}$, 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.

E2. 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

[46]In some counterfactuals, the household also receives a lump-sum tax or transfer to pay for any subsidies or receive any revenue from distortions.

to the calibration that uses our IV estimates of θ, θ^X and ε from Tables 1 and 5 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 C.1. 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.

We calibrate the model to match plant-level 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.[47] 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 and technologies, we randomly draw 300 plants from the corresponding sector in the ASI.[48] We then recover all the plant production parameters from market shares and input cost shares.[49] Finally, we infer the consumer preference parameters ω^Z, ω^Z_k and $\delta^Z_{c,k}$ from aggregate consumption shares.

E3. Multiple Varieties per Plant

An alternative interpretation of our empirical findings is that plants produce multiple varieties, each of which has its own potentially less flexible production function, but plants can substitute between the different products they produce when input prices change. How sensitive are our counterfactual results to this alternative interpretation? Answering this question precisely requires fully specifying and calibrating our general equilibrium model under the alternative set of assumptions. However, we can gauge the sensitivity of our results by considering a simplified model of one industry.

[47]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).

[48]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.

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

Table C.1: 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

We analyze how changes in relative input prices affect 1) the industry price index and 2) industry spending shares. If different models, 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.[50]

Consider the following industry model. There are N plants in the industry, each producing a fixed set of J varieties. The representative consumer has nested CES preferences over the output by plants i and varieties j given by:[51]

$$Q = \left(\sum_{i=1}^{N} Q_i^{\frac{\mu-1}{\mu}}\right)^{\frac{\mu}{\mu-1}}, \qquad Q_i = \left(\sum_{j=1}^{J} Q_{ij}^{\frac{\eta-1}{\eta}}\right)^{\frac{\eta}{\eta-1}}$$

Plants produce each variety Q_{ij} using two inputs, A and B. Each variety comes with its own "recipe", a_{ij} and b_{ij}, which specifies the required proportions of the two inputs:[52]

$$Q_{ij} = Z_{ij} \min \{a_{ij}A + b_{ij}B\}$$

As before, plants are perfectly competitive and take input as well as output prices as given when maximizing profits.

[50]The change in the industry price index and spending shares captures the direct impact of the change in relative input prices on marginal costs as well as any resulting reallocation of production across firms.

[51]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).

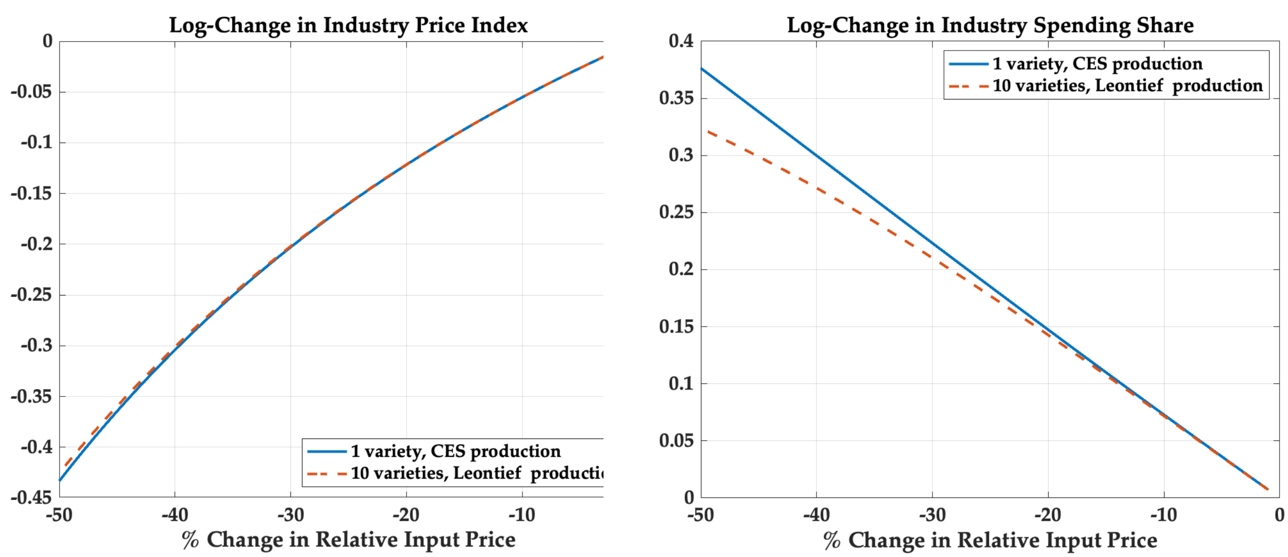
[52]We choose Leontief production within variety to show that our results are not sensitive even to this extreme case. More generally, one can think of variety j being produced by a CES production function: $Q_{ij} = Z_{ij}\left((a_{ij}A)^{\frac{\xi-1}{\xi}}, (b_{ij}B)^{\frac{\xi-1}{\xi}}\right)^{\frac{\xi}{\xi-1}}$. With a more intermediate value of ξ, such as Cobb-Douglas, the quantitative results are even closer to our benchmark model from Section 7..

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,r 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 two 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 production of each variety is Leontief.

Both researchers observe that the average relative spending share on input A across plants increases by 8.75% in response to a decrease in the relative price of input A by 6.25%.[53] Researcher 1 infers that $\theta = 2.4$, Researcher 2 infers that $\eta = 7.8$. 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 Figure C.1.

Figure C.1: Changes in Industry Price Index and Spending Shares in 2 Models



By construction, the changes in the industry price index and in the industry spend-

[53]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%.

ing share on input A overlap across models for small changes in relative input prices. Even for large changes in relative prices—up to a 50% reduction, similar to the counterfactuals we consider in Section 7.—, all three models yield qualitatively and quantitatively similar predictions.

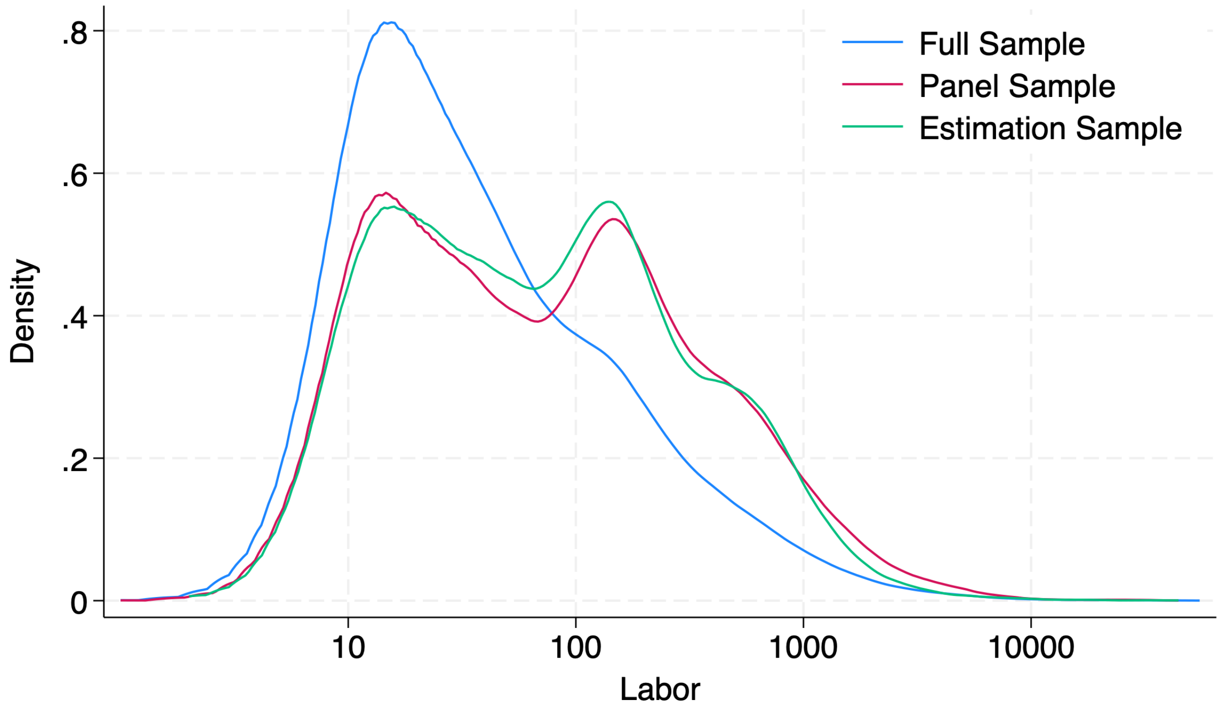
The change in the industry spending share is largest in the 1-variety model with CES production. This is because of the constant elasticity assumption. In the multiple-variety models, there is greater concavity in the industry spending share changes as plants gradually exhaust their ability to substitute across varieties.[54]

To summarize, in a model with Leontief production and multiple varieties per plant, productivity increases in individual sectors will, therefore, still be amplified through changes in the input-output structure, as in our quantitative model. However, this amplification may be somewhat dampened compared to our baseline estimates, especially for large changes.

[54]The rate at which this concavity sets in is increasing in the elasticity of substitution across varieties η.

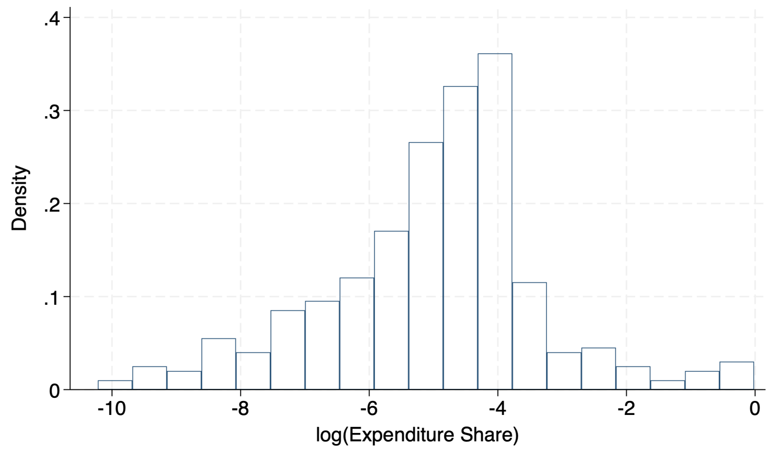
F Appendix Figures

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



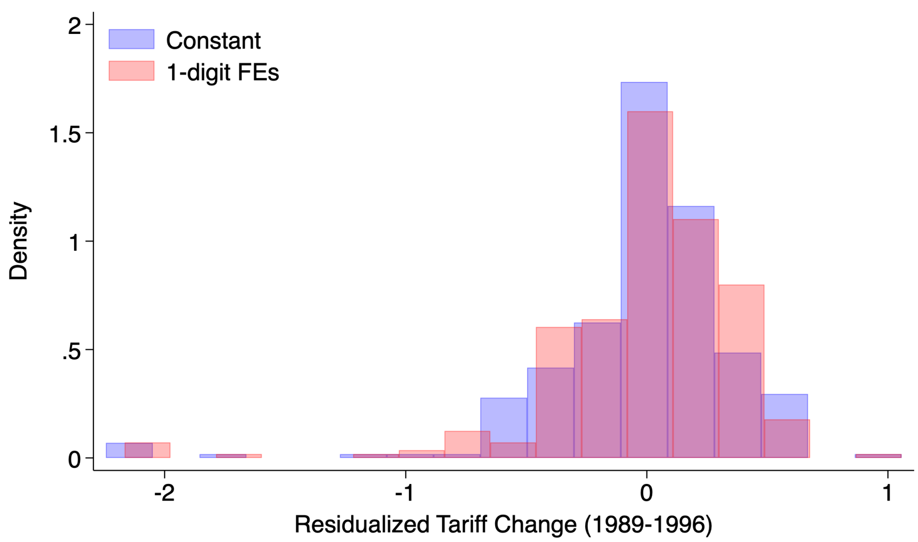
Notes: The figure shows the kernel density plots (with a bandwidth of 0.1) of labor in the 'Full Sample' of ASI plants, in the 'Panel Sample' and in the 'Estimation Sample'. We pool the years 1989 and 1996. Other summary statistics comparing the samples are shown in Table B.1.

Figure B.2: Histogram of Log(Spending Shares) on Material Input 'Textiles' in Industry 'Manufacture of Vegetable Oils and Fats Through 'Ghanis''



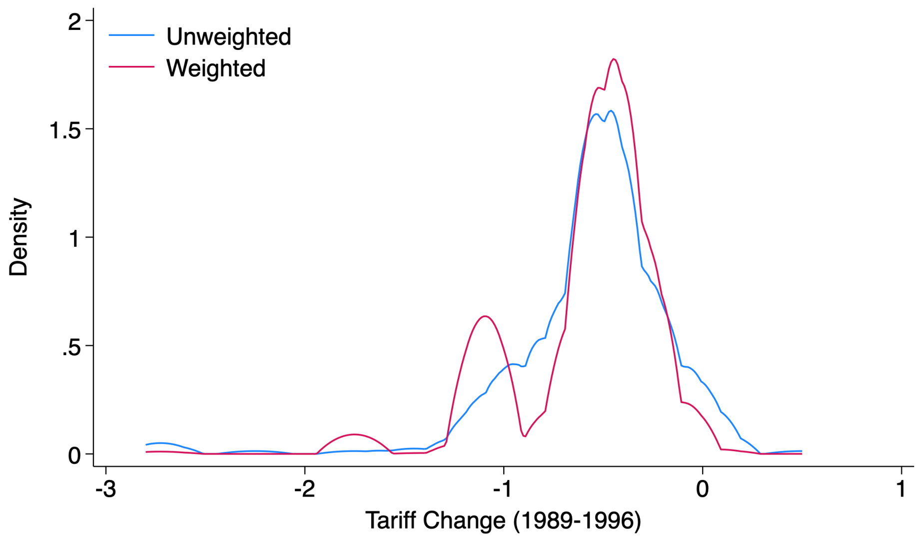
Notes: This figure is a histogram of log(spending shares) on the 1-digit ASICC category 'Textiles' in the industry 'Manufacture of Vegetable Oils and Fats Through 'Ghanis'' (NIC87 = 2111). The dispersion in shares is calculated in 1996 for 371 plants

Figure B.3: Distribution of Residualized Tariff Changes from 1989-1996



Notes: This figure plots histograms of tariff changes between 1989 and 1996 at the 5-digit ASICC level. The blue bars residualize the tariff changes on a constant, while the red bars residualize the tariff changes on 1-digit ASICC fixed effects. The standard deviations of the tariff changes are 0.41 and 0.39 respectively.

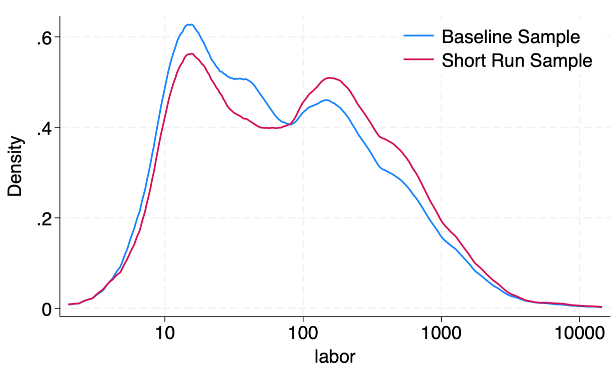
Figure B.4: Kernel Density Plot of Tariff Changes from 1989-1996



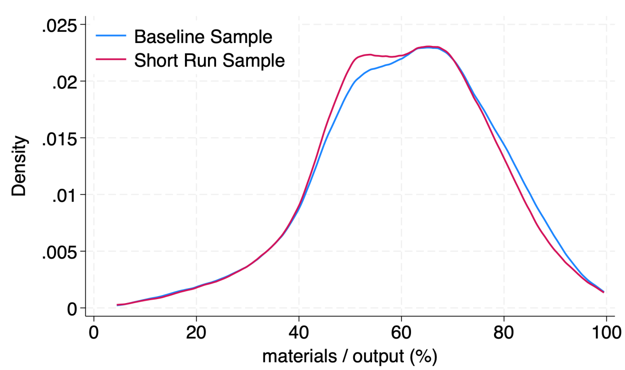
Notes: This figure plots kernel densities of tariff changes between 1989 and 1996 at the 5-digit ASICC level (not residualized). The blue line does not weight the tariff changes, while the red line weights tariff changes using the relevant importance weights from Borusyak et al. (2022). The standard deviations of the tariff changes are 0.40 and 0.37 respectively.

Figure B.5: Comparison of Short-Run and Baseline Estimation Samples

(a) Labor



(b) Materials Share



Notes:

Table B.1: ASI Sample Statistics

	Full Sample	Panel Plants	θ Estimation Sample
1989 ASI Survey			
# Plants	34,197	9,380	3,942
Median Age	11	12	12
Median/Mean Labor	23/92	38 / 184	39 / 161
Mean Materials share of intermediates	78.6%	80.0%	83.7%
Mean Intermediates share of output	82.2%	78.1	79.8%
Share of Aggregate Output	100%	51.2%	11.1%
Share of Aggregate Materials	100%	50.4%	10.6%
1996 ASI Survey			
# Plants	40,959	9,380	3,942
Median Age	12	19	18
Median/Mean Labor	22/83	33 / 173	35 / 150
Mean Materials share of intermediates	76.7%	76.6%	80.5%
Mean Intermediates share of output	76.2%	75.6%	78.0%
Share of Aggregate Output	100%	40.5%	9.3%
Share of Aggregate Materials	100%	40.3%	8.2%

Notes: The statistics reported are constructed from the 1989-90 and 1996-97 ASI surveys. The 'Full Sample' column reports statistics for all 'open' manufacturing plants within NIC87 industries 2000-3999 with non-missing output, labor, intermediates and age. The 'Panel Plants' column restricts the sample to plants that appear in 1989 and 1996. The 'Estimation Sample' column restricts the sample to panel plants that appear in our sample estimating θ. Changes in the sample between the 'Panel Plants' and 'Estimation Sample' columns result from dropping plants that import, as well as plants 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.

G Appendix Tables

Table B.2: Summary Statistics

Variable	Mean	Std. Dev.	P1	P10	P90	P99
Δln(spending share)	-0.00	1.04	-3.27	-1.06	1.10	3.18
Δln(price)	0.62	0.15	0.29	0.42	0.78	0.99
Δtariff	-0.58	0.29	-1.38	-1.10	-0.99	-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 10,142 observations and 3,942 plants in the final estimation sample.

Table B.3: Extensive Margin of Input Use at 1-digit Level

		Value Share		
	Share of Inputs	Median	Mean	Aggregate
Inputs Dropped	16.8%	1.6%	10.8%	3.4%
Inputs Added	25.4%	1.1%	8.7%	4.7%

Notes: The reported statistics are constructed from the 1989 and 1996 ASI surveys. The 'Inputs Dropped' row reports the (value) shares 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.4: 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
1989-1992 changes in:						
Input Tariffs	0.550	0.659	0.464	0.503	0.0456	0.0254
	(0.373)	(0.352)	(0.388)	(0.394)	(0.0308)	(0.0186)
	302	302	302	302	302	302
Output Tariffs	-0.231	0.0709	-0.298	-0.242	-0.0333	-0.00968
	(0.267)	(0.250)	(0.291)	(0.274)	(0.0228)	(0.0153)
	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)
1989-1992 changes in:						
Input Tariffs	0.0283	-0.278	0.0459	0.00530	-0.231	0.0135
	(0.0345)	(0.287)	(0.217)	(0.281)	(0.231)	(0.0511)
	270	270	302	302	302	270
Output Tariffs	-0.00177	-0.0288	0.0729	-0.0463	-0.0742	-0.0123
	(0.0207)	(0.159)	(0.148)	(0.192)	(0.163)	(0.0406)
	271	271	271	271	270	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.5: Early Tariff Changes 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	0.331	0.443	0.350	0.162	0.0421	0.008
	(0.407)	(0.375)	(0.426)	(0.428)	(0.037)	(0.021)
	302	302	302	302	302	302
Output Tariffs	-0.348	0.0493	-0.215	-0.426	-0.004	-0.029
	(0.354)	(0.314)	(0.381)	(0.372)	(0.031)	(0.020)
	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	0.0391	-0.406	-0.0907	-0.120	-0.403	0.0572
	(0.0404)	(0.321)	(0.216)	(0.285)	(0.276)	(0.0648)
	270	270	302	302	302	270
Output Tariffs	-0.00987	0.0430	0.0843	-0.0453	-0.0504	0.0147
	(0.0286)	(0.212)	(0.188)	(0.241)	(0.224)	(0.0483)
	271	271	271	271	270	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 1992 (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 use 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.

Table B.6: Balance tests at firm-input level

	Concordance %	Concordance %	1989 Price	1989 Price	# 5-digit inputs	# 5-digit inputs
	(1)	(2)	(3)	(4)	(5)	(6)
Δ tariffs	0.015	0.028	-0.017	-0.059	0.823	0.600
	(0.047)	(0.021)	(0.067)	(0.072)	(0.802)	(0.600)
Observations	10,144	10,144	8,605	8,605	9,014	9,014
# plants	3,943	3,943	3,905	3,905	3,923	3,923
# 5-digit inputs	297	297	302	302	297	297
1-digit input FEs	x	✓	x	✓	x	✓

Notes: This table shows various balance tests at the firm-input level with and without 1-digit input fixed effects. The 'Concordance %' columns use as the dependent variable the share of material expenditures in 1989 at the plant x 1-digit level that were concorded from the 1989 item code classification to the 3-digit or 5-digit ASICC input classification. The '1989 Price' columns use as dependent variable the average price deviation of 5-digit inputs used by the plant in 1989, where price deviations are taken relative to the median price for that input in the same industry in 1989. The '# 5-digit inputs' columns use as dependent variable the number of 5-digit ASICC inputs used by the plant in 1989. In all regressions, the regressor is the tariff instrument used in the baseline specification for Table 1. An observation is a plant $\times$ 1-digit material input category. We report exposure-robust standard errors from the equivalent tariff-level instrumental variable regressions for all regressions. For columns (1)-(2) / (3)-(4) / (5)-(6), the inverse of the Herfindahl index of the exposure weights is 33.3 / 31.3 / 31.1 , and the largest weight is 0.101 / 0.113 / 0.109.

Table B.7: Robustness to Timing of Tariff Changes and 1-digit Input Fixed Effects

	Baseline Sample				No Late Tariff Changes				Large Early Tariff Changes			
	No 1-digit FE		With 1-digit FE		No 1-digit FE		With 1-digit FE		No 1-digit FE		With 1-digit FE	
	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)	-0.30	-1.47	-0.39	-2.30	-0.61	-1.44	-0.56	-2.30	-0.69	-1.32	-0.83	-2.92
	(0.17)	(0.48)	(0.19)	(1.30)	(0.20)	(0.49)	(0.28)	(1.05)	(0.28)	(0.49)	(0.45)	(1.08)
Elasticity	1.3	2.47	1.39	3.30	1.61	2.44	1.56	3.30	1.69	2.32	1.83	3.92
First Stage												
Δtariffs		0.16		0.13		0.18		0.15		0.17		0.15
		(0.038)		(0.037)		(0.037)		(0.036)		(0.032)		(0.033)
F-stat		18.0		11.6		22.7		16.8		26.9		19.4
Observations	10,144	10,144	10,144	10,144	6,243	6,243	6,243	6,243	3,118	3,118	3,118	3,118
# plants	3,943	3,943	3,943	3,943	3,773	3,773	3,773	3,773	1,334	1,334	1,334	1,334
# 5-digit ASICC inputs	297	297	297	297	289	289	289	289	280	280	280	280

Notes: This table shows our estimation results with and without 1-digit input fixed effects for different sample restrictions. The 'Baseline Sample' columns include all observations in the baseline sample as described in the main text. The 'No Late Tariff Changes' columns drops plant-input observations where there was decline in tariffs greater than 20pp between 1994 and 1996 that accounted for at least 50% of the overall tariff decline from 1989 to 1996 for that plant-input. The 'Large Early Tariff Changes' imposes the additional restriction of only keeping plants plants for whom the standard deviation of 1989-1992 tariff changes across their 1-digit inputs is above the median. The dependent variable in the OLS and IV specifications is 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. We report exposure-robust standard errors from the equivalent tariff-level instrumental variable regressions for the first-stage and IV specifications, and cluster at the 4-digit industry level for OLS regressions. For columns (1)-(4) / (5)-(8) / (9)-(12), the inverse of the Herfindahl index of the exposure weights is 33.3 / 21.2 / 23.1 , and the largest weight is 0.101 / 0.138 / 0.153.

Table B.8: 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)	-0.19	-2.33	-0.52	-0.44	-0.69	-1.86	0.12	0.45
	(0.15)	(0.54)	(0.40)	(1.00)	(0.20)	(0.50)	(0.24)	(1.22)
Elasticity ($\hat{\theta}$)	1.19	3.33	1.52	1.44	1.69	2.86	0.88	0.56
First Stage								
Δtariffs		0.17		0.15		0.17		0.14
		(0.044)		(0.036)		(0.028)		(0.06)
F-stat		14.5		17.2		38.8		6.0
Observations	7,583	7,583	2,561	2,561	5,236	5,236	3,737	3,737
# plants	2,876	2,876	1,067	1,067	1,962	1,962	1,570	1,570
# 5-d inputs	284	284	266	266	267	267	273	273

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 B. 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. All regressions include plant fixed effects. Regressions are weighted by the inverse of the number of inputs used by the plant. The OLS standard errors are clustered at the 4-digit industry level. We report exposure-robust standard errors from the equivalent tariff-level instrumental variable regressions for the first-stage and IV specifications. For columns (1)-(2) / (3)-(4) / (5)-(6) / (7)-(8), the inverse of the Herfindahl index of the exposure weights is 26.8 / 28.0 / 18.8 / 39.2, and the largest weight is 0.129 / 0.138 / 0.161 / 0.074.

Table B.9: Robustness of θ Estimates

	3-digit Clustering		Top 3 Inputs		Value Share > 1%		No Extensive Margin		With importers		Laspeyres Price Index	
	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)	-0.30	-1.47	-0.31	-1.48	-0.27	-1.87	-0.27	-1.58	-0.27	-1.41	-0.42	-1.37
	(0.17)	(0.52)	(0.18)	(0.52)	(0.24)	(0.74)	(0.24)	(0.75)	(0.15)	(0.54)	(0.17)	(0.46)
Elasticity ($\hat{\theta}$)	1.30	2.47	1.31	2.48	1.27	2.87	1.27	2.58	1.27	2.41	1.42	2.37
First Stage												
Δtariffs		0.16		0.16		0.14		0.160		0.16		0.17
		(0.038)		(0.038)		(0.041)		(0.037)		(0.038)		(0.040)
F-stat		18.0		16.2		12.3		19.1		16.4		18.6
Observations	10,144	10,144	9,504	9,504	8,113	8,113	3,220	3,220	13,2753	13,275	10,144	10,144
# plants	3,943	3,943	3,943	3,943	3,943	3,943	1,200	1,200	5,150	5,150	3,943	3,943
# 5d inputs	297	297	297	297	297	297	282	282	304	304	297	297

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. We report exposure-robust standard errors from the equivalent tariff-level instrumental variable regressions for the first-stage and IV specifications, and cluster at the 4-digit industry-level for the OLS specifications. For columns (1)-(2) / (3)-(4) / (5)-(6) / (7)-(8) / (9)-(10) / (11)-(12), the inverse of the Herfindahl index of the exposure weights is 24.2 / 32.7 / 37.0 / 25.4 / 37.4 / 33.3, and the largest weight is 0.102 / 0.105 / 0.099 / 0.135 / 0.083 / 0.101. All regressions include plant fixed effects. Regressions are weighted by the inverse of the number of inputs used by the plant. The '3-digit Clustering' uses exposure-robust standard errors clustered at the 3-digit ASICC level. 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 'Value Share > 1%' specification restricts the set of inputs to those that account for at least 1% of plant expenditures (averaged between 1989 and 1996). 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 'With importers' specification does not restrict the sample to plants that don't import. The 'Laspeyres Price Index' specification constructs the plant-specific price index using 1989 expenditure shares, as opposed to the average of 1989-1996 shares as we do for the baseline.

Table B.10: Small vs. Large Plants

	Below Median Materials		Above Median Materials	
	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)
Δln(prices)	-0.28	-1.92	-0.32	-1.21
	(0.23)	(0.74)	(0.22)	(0.44)
Elasticity	1.28	2.92	1.32	2.21
First Stage				
Δtariffs		0.14		0.18
		(0.039)		(0.037)
F-stat		12.3		22.4
Observations	4,918	4,918	5,226	5,226
# plants	1,971	1,971	1,971	1,971
# 5-d inputs	293	293	290	290

Notes: This table shows our estimation results separately for small and large plants (measured by their expenditure on materials). 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. We report exposure-robust standard errors from the equivalent tariff-level instrumental variable regressions for the first-stage and IV specifications, and cluster at the 4-digit industry-level for the OLS specifications. For small (large) plants, the inverse of the Herfindahl index of the exposure weights is 38.4 (26.8), and the largest weight is 0.080 (0.122). All regressions include plant fixed effects. Regressions are weighted by the inverse of the number of inputs used by the plant.

Table B.11: Additional Robustness of θ Estimates

	1% Tariff Trimming		2% Trimming		Industry Exposures		Concordance$>95\%$		Aggregate 3-d Shares		ln(1+tariffs)	
	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)	-0.30	-1.45	-0.29	-1.28	-0.32	-0.54	-0.29	-1.53	-0.19	-1.37	-0.30	-1.30
	(0.17)	(0.36)	(0.17)	(0.45)	(0.16)	(0.52)	(0.18)	(0.43)	(0.21)	(0.44)	(0.17)	(0.49)
Elasticity ($\hat{\theta}$)	1.30	2.45	1.29	2.28	1.32	1.54	1.29	2.53	1.19	2.37	1.30	2.30
First Stage												
Δtariffs		0.13		0.16		0.20		0.16		0.19		0.33
		(0.023)		(0.039)		(0.040)		(0.037)		(0.030)		(0.075)
F-stat		32.8		15.0		23.4		19.7		40.1		19.5
Observations	10,958	10,958	9,384	9,384	10,144	10,144	9,448	9,448	10,144	10,144	10,144	10,144
# plants	4,149	4,149	3,714	3,714	3,943	3,943	3,673	3,673	3,943	3,943	3,943	3,943
# 3-d inputs	300	300	294	294	305	305	294	294	302	302	297	297

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. The OLS standard errors are clustered at the 4-digit industry level. We report exposure-robust standard errors from the equivalent tariff-level instrumental variable regressions for the first-stage and IV specifications. All regressions include plant fixed effects. Regressions are weighted by the inverse of the number of inputs used by the plant. The '1% Tariff Trimming' specification does not trim the 5% left tail of tariff changes, as we do for the baseline specification, but simply trims the 1% tail. The '2% Trimming' specification trims the 2% tails of prices, tariffs and value shares rather than 1% shares. The 'Industry Exposures' specification constructs prices and tariffs using average industry rather than plant-specific shares. The 'Concordance$>95\%$' specification restricts the sample to plants for which at least 95% of material expenditures in 1989 were concorded to the ASICC classification. The 'Aggregate 3-d Shares' constructs the price and tariff variables using plant-specific 3-digit expenditure shares but aggregate 5-digit expenditure shares within each 3-digit category. The 'ln(1+tariffs)' specification construct the tariff variable as $\Delta\ln(1+\tau_{ik})$ rather than $\Delta\tau_{ik}$. For columns (1)-(2) / (3)-(4) / (5)-(6) / (7)-(8) / (9)-(10) / (11)-(12), the inverse of the Herfindahl index of the exposure weights is 32.9 / 31.1 / 33.8 / 31.8 / 32.8 / 33.3, and the largest weight is 0.093 / 0.105 / 0.099 / 0.107 / 0.101 / 0.101.

Table B.12: Short-Run vs. Long-Run Elasticity Estimates, with 1-digit FEs

	Short-Run: 1989-1993/94				Long-Run: 1989-1996			
	No 1-digit FEs		With 1-digit FEs		No 1-digit FEs		With 1-digit FEs	
	OLS	IV	OLS	IV	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Δln(prices)	0.26	0.31	0.05	-0.57	-0.69	-1.32	-0.83	-2.92
	(0.27)	(0.61)	(0.30)	(0.70)	(0.28)	(0.49)	(0.45)	(1.08)
Elasticity	0.74	0.69	0.95	1.57	1.69	2.32	1.83	3.92
First Stage								
Δtariffs		0.12		0.11		0.17		0.15
		(0.029)		(0.043)		(0.033)		(0.033)
F-stat		16.6		6.7		26.9		19.4
Observations	3,676	3,676	3,676	3,676	3,118	3,118	3,118	3,118
# plants	1,008	1,008	1,008	1,008	1,334	1,334	1,334	1,334
# 5-d inputs	272	272	272	272	280	280	280	280

Notes: This table shows our short-run estimation results from the specifications shown in equations 8 and 9, as well as our long-run estimation results from the specifications in equations 4 and 5. In columns (1)-(4) an observation is a plant $\times$ year $\times$ 1-digit material input category. In columns (5)-(8) an observation is a plant $\times$ 1-digit material input category. The sample for all columns only includes plants that experienced large relative tariff changes in the first year of the liberalization, and excludes any plant-inputs where there were large tariff changes between 1994 and 1996. The dependent variable in columns (1)-(4) are the change in plant spending shares between 1989 and either 1993 or 1994. The dependent variable in columns (5)-(8) 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 at the 1-digit ASICC input level. All regressions include plant fixed effects. Columns (1)-(4) include plant $\times$ year fixed effects. Columns (3), (4), (7) and (8) include year $\times$ 1-digit ASICC input fixed effects. Regressions are weighted by the inverse of the number of inputs used by the plant; each plant is weighted equally. The OLS standard errors are clustered at the 4-digit industry level. We report exposure-robust standard errors from the equivalent tariff-level instrumental variable regressions for the first-stage and IV specifications. For the short-run (long-run) horizon estimates, the inverse of the Herfindahl index of the exposure weights is 23.1 (23.1), and the largest weight is 0.147 (0.153).

Table B.13: Short-Run Elasticity Estimates with Commodity Price IV - with 1-digit FEs

	1-year horizon				2-year horizon			
	No 1-digit FEs		With 1-digit FEs		No 1-digit FEs		With 1-digit FEs	
	OLS	IV	OLS	IV	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Δln(prices)	0.091	0.479	0.091	0.632	0.038	0.518	0.038	0.656
	(0.047)	(0.282)	(0.051)	(0.546)	(0.046)	(0.304)	(0.046)	(0.698)
Elasticity	0.909	0.521	0.909	0.368	0.962	0.482	0.962	0.344
	[0.8, 1.0]	[0.0, 1.1]	[0.8, 1.0]	[-0.7, 1.4]	[0.9, 1.1]	[-0.1, 1.1]	[0.9, 1.1]	[-1.0, 1.7]
First Stage								
Δtariffs		0.176		0.100		0.258		0.149
		(0.046)		(0.0313)		(0.097)		(0.070)
F-stat		14.6		10.2		7.0		4.6
Observations	76,982	76,982	76,982	76,982	42,056	42,056	42,056	42,056
# plants	18,622	18,622	18,622	18,622	10,666	10,666	10,666	10,666
# 5-d inputs	94	94	94	94	92	92	92	92

Notes: This table shows our short-run estimation results using global commodity price fluctuations as an instrument, from the specifications shown in equations 12 and 13. An observation is a plant $\times$ year $\times$ 1-digit material input category. The sample includes plant in the ASI survey waves from 1999 to 2013. The dependent variable is the log-change in plant spending shares. The dependent variable in the first stage is the change in plant material input price at the 1-digit ASICC input level. All regressions include plant x year fixed effects and controls for plant expenditure share on commodities within each 1-digit ASICC category, interacted with year fixed effects. Columns (3), (4), (7) and (8) include year $\times$ 1-digit ASICC input fixed effects. Regressions are weighted by the inverse of the number of inputs used by the plant; each plant is weighted equally. The OLS standard errors are clustered at the 4-digit industry level. We report exposure-robust standard errors from the equivalent year x 5-digit input level instrumental variable regressions for the first-stage and IV specifications, clustered at the 5-digit ASICC input level. For the 1-year (2-year) horizon results, the inverse of the Herfindahl index of the exposure weights is 81.3 (74.8), and the largest weight is 0.042 (0.038).

Table B.14: 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)	0.77	0.36	0.42	0.06	0.50	0.34
	(0.24)	(0.35)	(0.13)	(0.57)	(0.21)	(0.28)
Elasticity	0.23	0.64	0.58	0.98	0.50	0.66
First Stage						
Δtariffs		0.13		0.10		0.16
		(0.032)		(0.039)		(0.039)
F-stat		15.9		6.4		17.6
Observations	7,638	7,638	13,330	13,330	12,456	12,456
# plants	3,861	3,861	6,813	6,813	6,366	6,366
# 5-d inputs	310	310	309	309	310	310

Notes: This table reports robustness checks for our baseline estimates of θ^X from 21 and 22.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. Regressions are weighted by the inverse of the number of inputs used by the plant; each plant is weighted equally. The OLS standard errors are clustered at the 4-digit industry level. We report exposure-robust standard errors from the equivalent tariff-level instrumental variable regressions for the first-stage and IV 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. For columns (1)-(2) / (3)-(4) / (5)-(6), the inverse of the Herfindahl index of the exposure weights is 30.8 / 47.6 / 44.6, and the largest weight is 0.142 / 0.084 / 0.089.

Table B.15: 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)	0.75	0.08	0.36	-0.20	0.52	0.23
	(0.32)	(0.52)	(0.13)	(0.93)	(0.18)	(0.45)
Elasticity	0.25	0.92	0.64	1.20	0.48	0.77
First Stage						
Δtariffs		0.11		0.079		0.13
		(0.023)		(0.034)		(0.034)
F-stat		21.1		5.5		16.0
Observations	3,784	3,784	6,671	6,671	6,213	6,213
# 5-d inputs	307	307	309	309	307	307

Notes: This table reports robustness checks for our baseline estimates of ε from 23 and 24.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. The OLS standard errors are clustered at the 4-digit industry level. We report exposure-robust standard errors from the equivalent tariff-level instrumental variable regressions for the first-stage and IV 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. For columns (1)-(2) / (3)-(4) / (5)-(6), the inverse of the Herfindahl index of the exposure weights is 30.3 / 47.5 / 44.4, and the largest weight is 0.144 / 0.084 / 0.090.

Table B.16: Alternate Nesting Structures

	Materials vs. Labor		Materials vs. Capital		Materials vs. Energy		Materials vs. Services		Materials vs. Capital & Labor		Disaggregated Material Categories		Industry Materials Elasticity	
	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Δln(prices)	0.24	-0.04	0.74	0.91	0.59	-0.00	0.47	0.69	0.67	0.72	-0.39	-1.51	-0.43	-2.26
	(0.04)	(0.56)	(0.28)	(0.72)	(0.21)	(0.40)	(0.21)	(0.38)	(0.17)	(0.37)	(0.02)	(0.63)	(0.30)	(1.13)
Elasticity	0.76	1.04	0.26	0.09	0.41	1.00	0.53	0.31	0.33	0.28	1.39	2.51	1.43	3.26
First Stage														
Δtariffs		0.09		0.14		0.15		0.16		0.13		0.16		0.19
		(0.026)		(0.021)		(0.033)		(0.041)		(0.023)		(0.038)		(0.07)
F-stat		11.5		31.5		20.6		15.7		32.6		16.7		7.1
Observations	6,439	6,439	6,563	6,563	6,635	6,635	6,695	6,695	6,568	6,568	10,432	10,432	1,260	1,260
# 5-digit ASICC inputs	312	312	309	309	309	309	309	309	309	309	294	294	310	310

Notes: This table shows our estimation results for elasticities of substitution corresponding to alternate nesting structures from the baseline. The first 10 columns estimate the elasticity of substitution between materials and various other inputs as specified by the column titles. The 'Disaggregated Material Categories' columns report results for a more disaggregated set of material inputs than the 1-digit ASICC categories used in the baseline. The 'Industry Materials Elasticity' columns estimate the industry-level elasticity of substitution between 1-digit material inputs. In all specifications we report exposure-robust standard errors from the equivalent tariff-level instrumental variable regressions for the first-stage and IV specifications, and cluster at the 4-digit industry level for OLS regressions. For columns (1)-(2) / (3)-(4) / (5)-(6) / (7)-(8) / (9)-(10) / (11)-(12) / (13)-(14), the inverse of the Herfindahl index of the exposure weights is 49.6 / 49.6 / 48.5 / 46.5 / 49.6 / 33.6 / 39.6 , and the largest weight is 0.085 / 0.085 / 0.084 / 0.084 / 0.085 / 0.101 / 0.100.