Inputs, networks and quality-upgrading: Evidence from China in India

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This paper exploits China's accession to the WTO to investigate the propagation of a supply shock across the Indian production network. Consistent with a model of multi-product manufacturers gaining access to higher-quality components, a fall in input tariffs raises revenue, quality and prices whilst lowering quality-adjusted prices and the probability of product exit. Upgrading persists for at least ten years; at the peak in 2010, products with a 10% higher pre-accession input tariff, and hence a larger post-accession fall in tariffs, have 5.3% higher quality. This in turn raises quality further down the supply chain, with input-output linkages amplifying the one-step effect by up to 75%. In contrast to existing literature focused on negative demand effects of the 'China shock', these results highlight a potential beneficial impact in developing countries, namely supply-driven quality upgrading.

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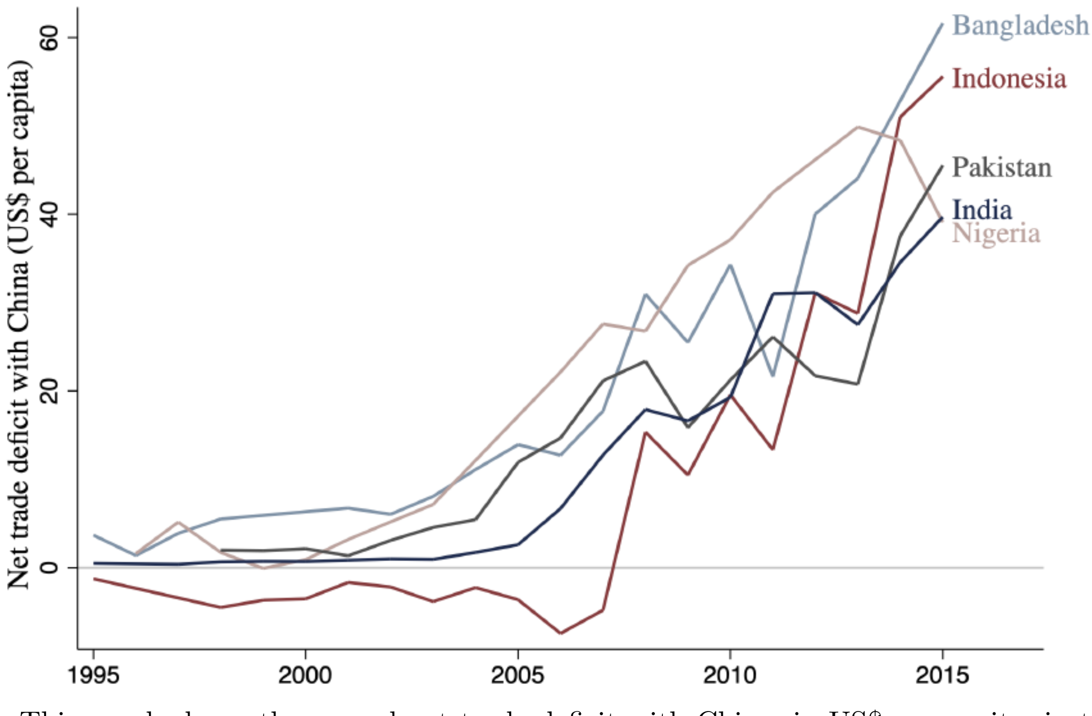
1 Introduction

China's rapid industrial expansion since 2000 has had repercussions across global markets. The negative effects on manufacturing in the USA, among other developed countries, have been widely studied (e.g. Autor et al. 2013, Bloom et al. 2019). Yet the implications are far broader: more than three billion people live in emerging economies that have developed large trade deficits with China since 2000. Figure 1.1 shows the per capita bilateral deficit with China in the next five largest developing countries: the rapid takeoffs in these deficits are striking, and strikingly similar.[1] Moreover, the composition of the imports from China driving these deficits is markedly different from the US story (Figure 1.2). In the USA, the rise in Chinese imports is mostly capital and consumption goods. In contrast, in large developing countries it is imports of intermediate inputs – i.e. parts and components yet to be assembled into final products – that are dominant, and that grow the fastest.

Figure 1.1: Bilateral per capita trade deficits with China

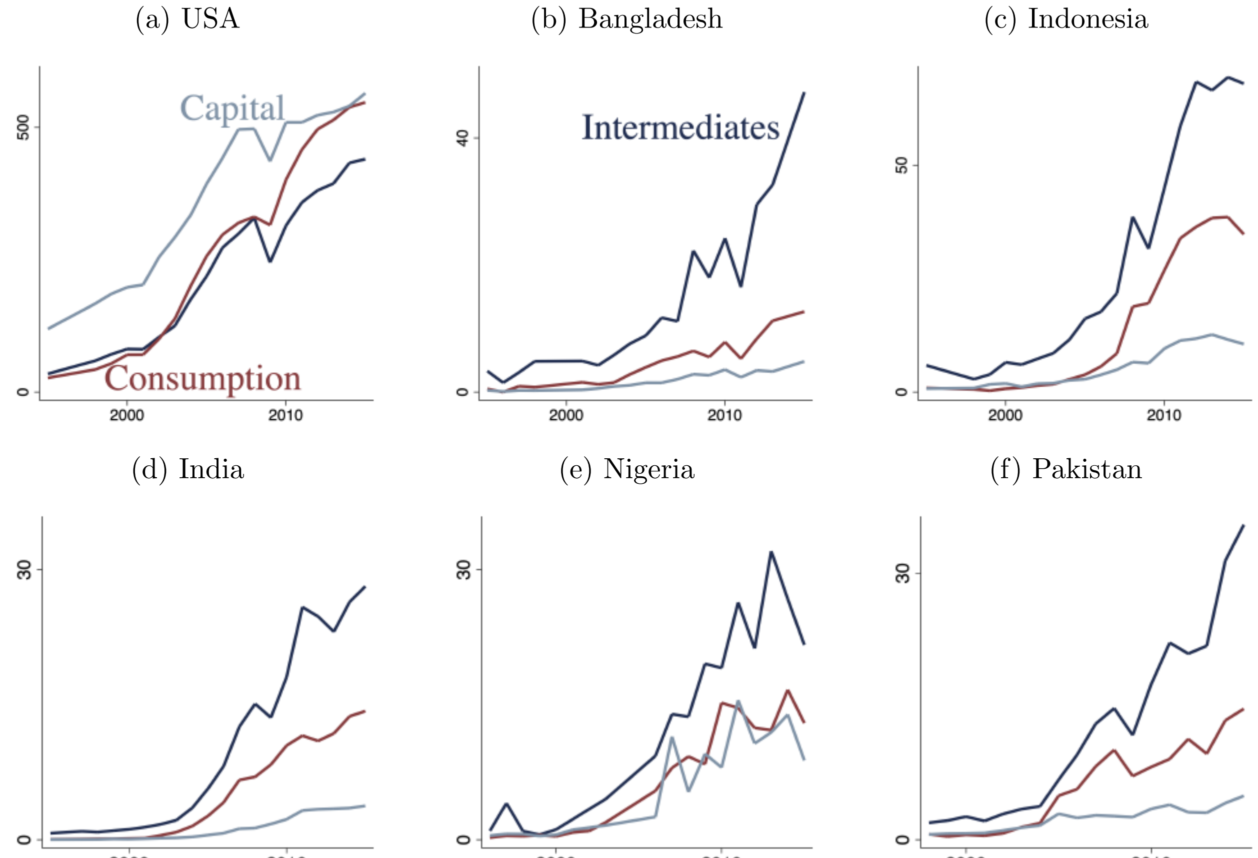


Notes: This graph shows the annual net trade deficit with China, in US$ per capita, in the five largest developing countries (excluding China itself, and excluding Brazil – which is, in contrast, predominantly a commodity exporter to China, as examined in Costa et al. (2016)). *Source:* UN Comtrade.

How did this sudden flood of Chinese components affect manufacturing firms in developing

[1] I exclude Brazil, which – as a major commodity exporter to China – has a different pattern, examined in Costa et al. (2016).

Figure 1.2: Total imports from China by type of good, US$ per capita



Notes: These graphs show countries' respective imports from China, in US$ per capita, split by end use. Goods are divided into three categories – specifically consumption goods, intermediate goods and capital goods – according to the UN's Broad Economic Categories classification (Revision 4). *Source:* UN Comtrade.

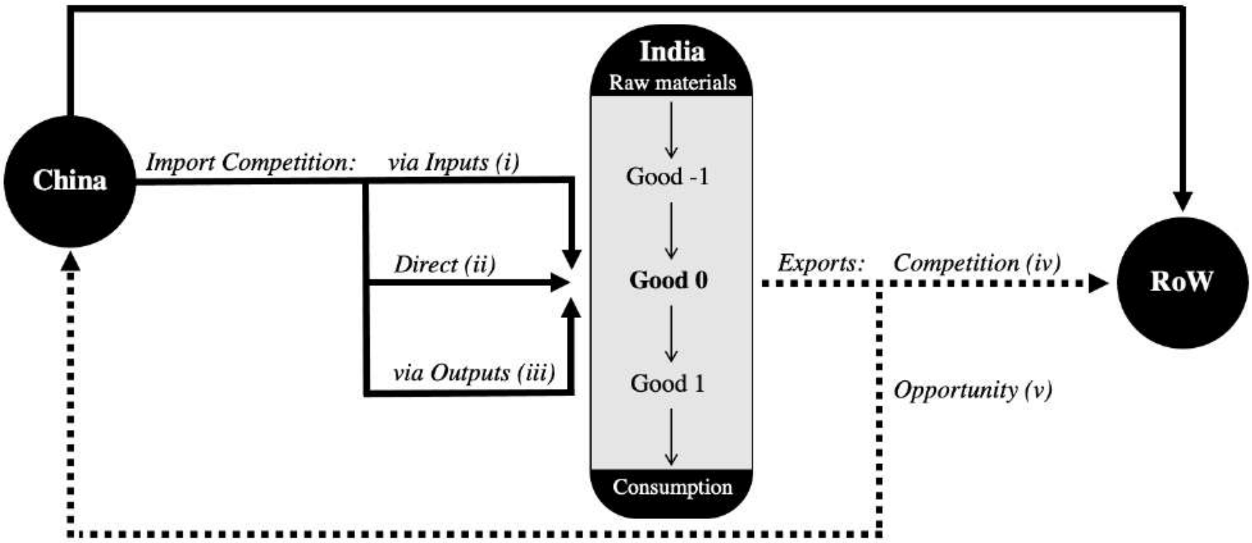
countries? I address this question using firm-product-level data from India, by far the largest of these trade partners.[2] Given the lack of linked customs-firm data, the first challenge is to isolate the effect of these inputs from other impacts of China's expansion. Figure 1.3 provides an overview of the key channels, from the perspective of a single product, Good 0, embedded within a supply chain in India. New Chinese inputs compete with existing inputs, improving the price and/or quality of Good -1 available for use in Good 0. Yet Chinese imports may also compete directly with Good 0, as is the focus of import competition studies (e.g. Autor et al. 2013). In addition, such imports could reduce demand for Good 0 as a component, by competing with domestic producers of the final consumption good, Good 1.[3] Further

[2]This scale is reflected in the size of the resulting trade deficit with China, which grew from less than $1bn in 2000 to more than $50bn in 2015.

[3]Such 'upstream' spillovers of import competition, where shocks to customers affect those who supply them, are considered in Acemoglu, Akcigit & Kerr (2015) and Acemoglu, Autor, Dorn, Hanson & Price (2016). I label this the 'output channel' throughout this paper to avoid any ambiguity arising from the fact that, in Figure 1.3, Good 1 is the downstream good.

competition occurs in export markets, as Indian producers face new Chinese competition when selling into the OECD, for example.[4] Lastly, Indian exporters can also export to the Chinese domestic market – although Indian exports to China are far smaller than the reverse, as already noted.[5][6]

Figure 1.3: China's growth & Indian manufacturing firms – five channels



Notes: This figure provides an overview of five channels through which China's accession to the WTO could affect Indian manufacturing firms. Thin lines depict the Indian manufacturing supply chain, thick lines represent China's exports, and dotted lines represent India's exports. China's expansion could affect a particular product, Good 0, by: (i) increasing competition in the market for inputs, i.e. Good -1; (ii) increasing competition directly in the domestic market for Good 0; (iii) increasing competition in the market for those final products Good 1 for which Good 0 is itself an intermediate input; (iv) increasing competition in the export market for Good 0; and/or (v) providing new demand or opportunities to export to the Chinese market.

To gauge the effects through each of these channels, I exploit China's accession to the WTO in 2001 and the resulting changes in tariffs. For the input and output effects (channels (i) and (iii) in Figure 1.3), I use detailed input-output shares from the Indian Ministry of Statistics and Programme Implementation (MoSPI) to calculate the average reduction in Indian tariffs on relevant inputs and outputs respectively. I supplement this identification strategy with an alternative method, following Autor, Dorn and Hanson (2013, hereafter ADH) which uses changes in trade flows between China and a basket of Southeast Asian

[4]Caselli et al. (2018) and Branstetter et al. (2019) find significant effects of Chinese competition through this indirect channel, for Mexican and Portuguese exporters respectively.

[5]Again, this channel is, in contrast, important for Brazil (Costa et al. 2016).

[6]The five channels shown in Figure 1.3 are clearly not exhaustive. For instance, there could be input or output effects related to channels (iv) or (v). I focus on import effects because these were important during India's tariff liberalisation in the early 1990s (e.g. Goldberg, Khandelwal, Pavcnik & Topalova 2010*a*, Topalova & Khandelwal 2010, De Loecker et al. 2016), while goods exports (especially to China) are a relatively small share of India's GDP.

countries to isolate plausibly exogenous changes in Chinese import competition and export opportunities.

Guided by a simple model of multi-product manufacturers, I then assess the impact of improved access to intermediates from China on a range of firm outcomes. I find that a fall in the tariffs on a firm's inputs raises revenue, quality and prices whilst lowering quality-adjusted prices and the probability of product exit, consistent with the theoretical predictions. In the main specification, following Lu & Yu (2015), a 10% higher average tariff on input industries in 2001, and hence a larger post-accession fall in tariffs, corresponds to a 2.4% rise in quality and a 1.9% rise in price in the post-accession period. This 'quality in, quality out' upgrading effect contrasts with previous 'demand-pull' (e.g. Verhoogen 2008) and 'escape competition' (Amiti & Khandelwal 2013) quality-upgrading mechanisms. It has a similar flavour to previous 'variety in, variety out' findings on product scope across India's trade liberalisation in the early 1990s (Goldberg, Khandelwal, Pavcnik & Topalova 2010*a*, Goldberg, Khandelwal & Pavcnik 2010), but differs in focusing on the intensive rather than the extensive margin.[7]

This supply-driven quality-upgrading result is robust to various alternative specifications. It holds both when estimating quality directly using the method of Khandelwal et al. (2013), and when inferring quality from observables (as in e.g. Verhoogen 2008, Kugler & Verhoogen 2012) or using standard firm-level measures of productivity (e.g. Ackerberg et al. 2015). Likewise I find similar results with the alternative identification mechanism inspired by ADH, and when using various combinations of controls and fixed effects. I also draw on the geographic collocation measure of Acemoglu, Akcigit & Kerr (2015) to confirm that the upgrading effect is indeed driven by production linkages *per se*, rather than simply proxying for the tendency of related industries to locate close to one another. Comparing the input channel to measures of the four others in Figure 1.3, I find that its effects are relatively significant and relatively important – as expected from the composition of Indian imports from China. Disaggregating, quality upgrading occurs only in medium and large firms, suggesting the presence of fixed costs to adapting procurement to take advantage of newly available higher-quality inputs.

I then consider spillovers of the supply-driven quality-upgrading effect in two dimensions. First, it persists over time. Upgrading continues for at least ten years; at the peak in 2010, products with a 10% higher pre-accession input tariff, and hence a larger post-accession fall in tariffs, have 5.3% higher quality. Second, upgrading spreads to other firms. I use a novel

[7] I find that fewer than 20% of manufacturing goods produced after 2001 are new products, at the seven-digit level, and that the quality-upgrading effect holds even when excluding new products.

method to trace the propagation of the effect along the supply chain, and find a knock-on quality upgrade for the next product in line. In other words, access to better inputs (Good -1) raises quality not just of the product using them (Good 0), but also raises the quality of products for which Good 0 is itself a component (Good 1). When broadening the analysis to include all ripples throughout the input-output network, using coefficients of the Leontief inverse matrix, the peak upgrading effect is amplified by up to 75%. I thus find that the production network plays a major role in spreading the effects of the Chinese supply shock to other firms and industries whose immediate inputs are not themselves directly affected.

In sum, this paper finds evidence that China's integration with Indian supply chains drove a persistent and widely spread rise in quality, even as quality-adjusted prices fell. I then note the robust findings elsewhere that: (i) firms producing higher quality goods pay higher wages to their workers (e.g. Verhoogen 2008, Kugler & Verhoogen 2012), and (ii) quality upgrading is strongly associated with long-run growth and development (e.g. Grossman & Helpman 1991, Kremer 1993, Hausmann & Rodrik 2003, Rodrik 2006, Hidalgo et al. 2007, Matsuyama 2008, Khandelwal 2010, Lane 2019, Verhoogen 2020). Altogether, this suggests that the Indian population received important direct and indirect gains from trade from China's resurgence through the supply-driven quality-upgrading mechanism. From a policy perspective, this also highlights an additional source of potential benefits forgone by the 2019 decision to withdraw India from the Regional Comprehensive Economic Partnership with other large Asian economies.

This paper's main contribution to the literature is that the 'China shock' may have had important benefits for other developing countries through the supply-driven quality-upgrading mechanism, particularly when the amplifying role of the production network is taken into account. More than three billion people live in developing economies which have grown large trade deficits with China since 2000, and no previous paper considers this mechanism in detail. Along the way, I make three main theoretical and methodological innovations. First, I extend the multi-product firm model of Manova & Yu (2017) to allow a new 'quality in, quality out' mechanism. Second, I characterise five channels through which the 'China shock' can affect a country – where previous studies consider only two or three – and model their impact on a range of firm-level observables. I also extend standard import tariff and import competition measures (Schott 2002, Bernard & Jensen 2002) to create analogous measures for each of the other four channels. Finally, I develop a novel method for tracing ripple effects across a network, and use it to provide the first evidence on the degree of quality propagation along a supply chain.

The rest of this paper proceeds as follows. Section 2 situates the paper within the literature, Section 3 describes the data, and Section 4 outlines the model. Section 5 then details the empirical specification, and Section 6 presents baseline results on the supply-driven quality-upgrading mechanism. Section 7 explores the spillovers of this effect, specifically persistence over time and propagation across the production network. Section 8 concludes.

2 Literature

A growing recent literature considers the role of production networks in propagating and amplifying microeconomic shocks to have macroeconomic implications (Carvalho 2008, Acemoglu et al. 2012, Acemoglu, Ozdaglar & Tahbaz-Salehi 2016, Carvalho et al. 2020, Acemoglu & Tahbaz-Salehi 2020). Acemoglu, Akcigit & Kerr (2015) and Acemoglu, Autor, Dorn, Hanson & Price (2016) use this framework to examine the China shock in the USA, while Liu (2019) and Lane (2019) use a network lens to evaluate development policy in China and South Korea. This paper is closest to Acemoglu, Autor, Dorn, Hanson & Price (2016), but the key difference in the Indian context is that the China shock has a supply as well as a demand element, and indeed I find that the former has larger spillovers than the latter.[8]

Other papers investigating the impact of China's increased role in global trade during the 1990s and 2000s have so far largely focused on developed countries (Autor, Dorn & Hanson 2013, 2016, Autor, Dorn, Hanson & Song 2014, Autor, Dorn, Hanson & Majlesi 2016, Bloom, Draca & Van Reenen 2016, Pierce & Schott 2016, Amiti, Dai, Feenstra & Romalis 2017, Dauth, Findeisen & Suedekum 2017), with some work on China (Lu & Yu 2015, Brandt et al. 2017), Brazil (Costa et al. 2016), Mexico (Iacovone et al. 2013), Ecuador (Bas & Paunov 2020) and India (Barua 2015, 2016, Chai 2018). The paper by Costa et al. (2016) is closely related, in considering the upside of China's boom for a developing country. However, its focus on the export opportunity channel in Brazil is less applicable to India and other large developing countries, given that Bangladesh, India, Indonesia, Nigeria and Pakistan (the remainder of the largest eight countries in the world, after excluding China, the USA and Brazil) all have

[8]Investigating the spillovers of import competition, Acemoglu et al. (2015) show theoretically that demand shocks will mainly propagate upstream, while supply shocks will mainly propagate downstream. In their main model with Cobb-Douglas preferences and technologies, demand shocks *only* travel upstream and supply shocks *only* travel downstream. Generalisations of the model (e.g. Acemoglu, Ozdaglar & Tahbaz-Salehi 2016) suggest only limited effects in the opposing directions, and their empirical results support the Cobb-Douglas version.

large trade deficits with China, unlike Brazil. My finding that access to imported inputs has especially large benefits for large firms echoes the results from Iacovone et al. (2013) in Mexico and Bas & Paunov (2020) in Ecuador, while the relative granularity of the Indian input-output table allows me to investigate the network aspects of the upgrading mechanism. On India, this paper builds upon Barua (2015, 2016) and Orr (2018) by disentangling the five channels, considering input and output quality, and examining network effects.

A series of studies have focused on the import competition and imported input channels during the Indian tariff liberalisation of the 1990s. Goldberg, Khandelwal, Pavcnik & Topalova (2010*a*) consider the impact of declines in input tariffs, Goldberg, Khandelwal, Pavcnik & Topalova (2010*b*) consider declines in output tariffs, and Topalova (2010), Topalova & Khandelwal (2010) and De Loecker et al. (2016) consider both together.[9] Similarly, studies investigating the impact of tariff changes in other countries (e.g. Amiti & Konings 2007, Halpern et al. 2015) have focused on examining the import channels.[10] Studies on India's liberalisation have considered a range of dependent variables, e.g. product scope (Goldberg, Khandelwal, Pavcnik & Topalova 2010*a*,*b*), productivity (Krishna & Mitra 1998, Sivadasan 2009, Topalova & Khandelwal 2010), and poverty and employment (Hasan et al. 2007, Topalova 2007, 2010, Edmonds et al. 2010); none to date focus on quality and quality-adjusted prices as the main outcomes of interest.

Empirical studies usually deal with quality in four main ways. Those focusing on other dependent variables can use various controls to remove quality effects; e.g. De Loecker et al. (2016) proxy for input quality variation using output prices, market shares and other observable product and firm characteristics, utilising the 'O-Ring' assumption that production of high-quality goods requires high-quality inputs (Kremer 1993). Some studies have direct measures of quality, (e.g. Atkin et al. 2017, Bai, Gazze & Wang 2019, Bai, Barwick, Cao & Li 2019, Chen & Juvenal 2016, 2018, 2019, Hansman et al. 2017, Macchiavello & Miquel-Florensa 2017, 2019), but to date these are only available for a limited range of products, such as coffee, wines and rugs, so are not suitable for the type of large-scale sectoral effects considered here.[11] To investigate quality across the whole manufacturing sector, this paper primarily

[9]Purely domestic aspects of India's regulatory liberalisation, such as the elimination of small-scale industry promotion considered by Martin et al. (2017), are less relevant here.

[10]Investigations into declines in both input and output tariffs generally find that the former have larger effects. Muendler (2004) is an exception, while Schor (2004) and Brandt et al. (2017) find the two to have similar magnitude.

[11]These studies build on earlier work by Sutton (2000, 2004), Goldberg & Verboven (2001), Macchiavello (2010), Crozet et al. (2012) and Bai (2016), again with direct measures only in narrow markets, from machine tools to watermelons.

uses the approach of Khandelwal (2010) and Khandelwal et al. (2013). This imposes specific preferences, thus assuming that quantity and price have a certain relationship as given by the resulting demand function, then backs out quality as quantity conditional on price. Intuitively, a variety in which a higher quantity is consumed at the same price is judged to have a higher quality. Lastly, some studies (e.g. Verhoogen 2008, Kugler & Verhoogen 2012) use reduced-form relationships between price and other observables to argue indirectly for a quality mechanism, to avoid making the assumptions required for an explicit measure of quality. This paper also draws upon this approach: the results for revenue and prices, which are directly observable, support the quality-upgrading mechanism, even in models without the CES assumption, as in Appendix 9.

3 Data

This paper uses manufacturing data for the financial years 1998-99 to 2013-14 from the Indian Annual Survey of Industries (ASI), which contains all manufacturing plants larger than 100 workers and a representative sample of plants that either a) use electricity and employ more than 10 workers, or b) do not use electricity and employ more than 20 workers.[12][13] In the main specifications I focus on census firms to allow an examination of the product-exit margin, then in secondary results I also examine heterogeneity across the full firm-size distribution. Martin et al. (2017) examine the quality of the ASI panel data, e.g. by checking for consistency in opening and closing stock variables reported by the same establishment in consecutive years. They conclude that the data quality is consistent across state, industry, time and establishment size, and that the panel identifier correctly tracks each establishment across the years surveyed. Each plant in the ASI is asked to detail the product type, production quantity and net sale value for each of its top ten products, but incomplete data reporting means that product-level data are only available for a subset of factories, as shown in Table 3.1. Product type is reported at the five-digit ASI Commodities Code (ASICC) level prior to 2010, or at the seven-digit National Product Classification for Manufacturing Sector (NPCMS) thereafter.

I use annual bilateral tariffs from the UNCTAD Trade Analysis Information System (TRAINS), and annual bilateral trade flows from UN Comtrade. I use publicly available

[12] In the case of multi-plant firms, the ASI data does not record which plants belong to which firms; this paper therefore conducts the analysis at the level of plants and uses the terms 'plant' and 'firm' interchangeably.

[13] The ASI financial year runs from April to March; for convenience I label values for the 1998-99 financial year as 1998, and so on, throughout this paper.

Table 3.1: Comparison of subsets of data used

Mean		**Factory-level**	**Product-level**	**Trade-level**
Number of products		3.8	3.7	3.5
Fixed assets (INR million)		571	595	590
Working capital (INR million)		162	167	165
No. of employees		335	327	337
Ownership (%)	Private	92.2	91.9	93.4
	Joint	5.1	5.4	4.7
	Public	2.7	2.7	1.9
Location (%)	Urban	57.8	56.8	58.2
	Rural	42.2	43.2	41.8
Observations		546,913	353,383	215,287

concordances to map the ASICC codes onto NPCMS, the first five digits of which are identical to the UN's Central Product Classification (CPC). I then match these CPC codes to Harmonized System (HS) tariffs and import/export flows. Each of these mappings is imperfect, resulting in the smaller subset in the third column of Table 3.1. However, the table shows that firms which report product-level data, and whose product codes can be matched to trade data, are not substantially different from those only reporting factory-level data.[14]

Identifying variation comes from the fall in the tariffs on China's imports and exports following its accession to the WTO in 2001. India-China bilateral trade grew dramatically after 2001, shown in Figure 3.1 Panel (a), particularly Indian imports from China. Chinese exports to the OECD also grew dramatically, dwarfing those from India, as shown in Panel (b). Growing Chinese import competition over the period was predominantly concentrated in manufactures rather than primary commodities, as shown in Figure 3.2, with particular clusters in electronics, textiles and chemicals. The districts that most heavily used these products as inputs are clustered around urban centres in the north, west and south, as shown in Figure 3.3. These districts also saw the largest increases in quality (measured using the procedure outlined in Section 5.3), as shown in Figure 3.4.[15]

[14]The exact number of observations used in each regression in Section 6 varies with the particular dependent variable under consideration, as in each case the largest available dataset is used. For instance, the De Loecker et al. (2016) algorithm for calculating markups and marginal costs is particularly demanding, so there are fewer observations with sufficiently complete data to be included in the markup and marginal cost regressions.

[15]Since the ASI dataset with panel identifiers does not include district locations, unlike the annual cross-sectional dataset, locations are identified using the method of Martin et al. (2017) – specifically, matching firms across the two datasets on those variables which are common to both. Similarly, I use the mapping from Martin et al. (2017) to convert the (time-varying) district codes onto the 1998 district boundaries. Currently I only have access to a limited number of annual cross-sections, hence the limited timespan in the maps.

Examples of supply-driven quality upgrading: Anecdotally, supply-driven quality upgrading occurred in medium and large firms across industries.[16] Consider two examples: a young electric-vehicle startup, with only 30 production workers, and one of India's largest pharmaceutical firms, with 11,500 employees and more than half a billion USD in revenue.[17] The former produces swappable batteries for electric mopeds, autorickshaws and municipal buses. Each autorickshaw battery contains 14 lithium-ion cells, imported from China, which have fallen substantially in weight while improving in efficiency – allowing the assembled batteries to be lighter with a longer charge. The latter firm specialises in production of insulin for diabetes treatment, and imports many active ingredients and raw materials from China, primarily acids, alkalis, reagents and other basic chemical compounds. Since 2001, the price-adjusted rate of defects (e.g. the frequency of impurities or air bubbles in the chemicals, within any given price band) has fallen substantially – increasing safety, i.e. quality in this context.[18]

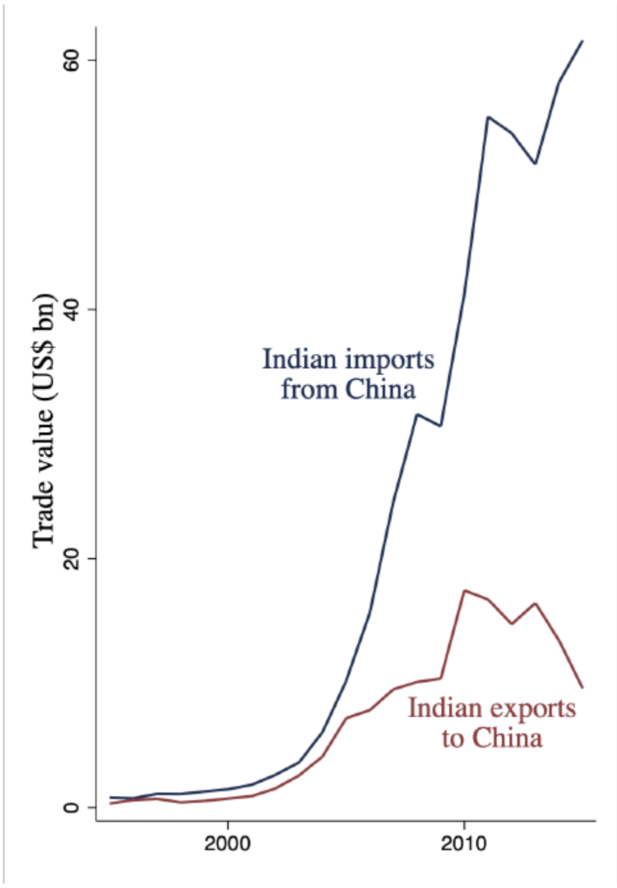
[16]The distribution of firms across sectors is shown in Table 10.7 in the Appendix, along with pictures from the two exemplar firms in Figures 10.1 and 10.2.

[17]Source: discussions with management in both companies, Bangalore and Delhi, January 2020.

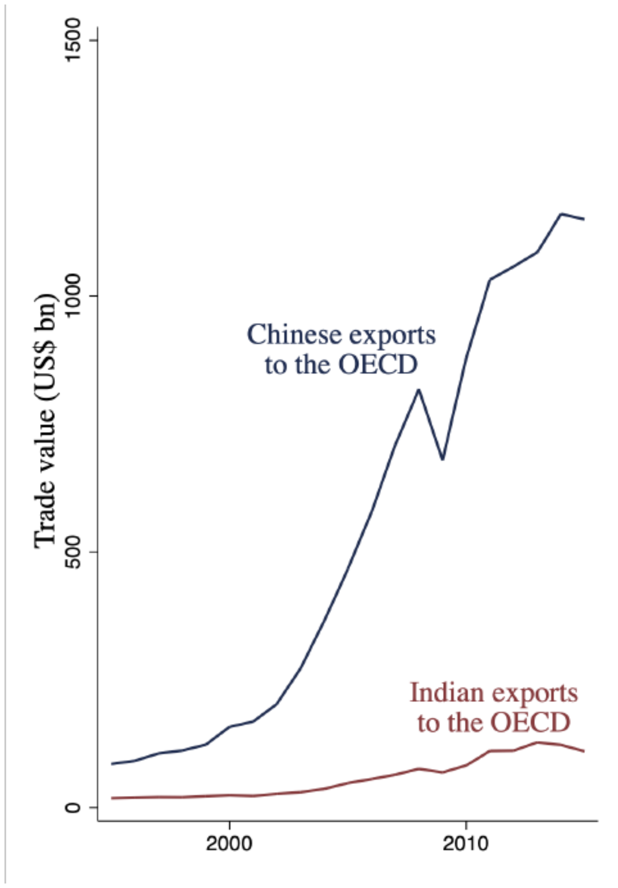
[18]Indeed, Chinese pharmaceutical inputs were so successful that they would later raise concerns about supply chain risk during the Covid-19 pandemic: by 2020, one in every three pills taken by an American was a generic drug produced in India, which in turn purchased 66% of all ingredients from China (Zakaria 2020).

Figure 3.1: Goods trade between India, China and the OECD

(a) India & China bilateral trade

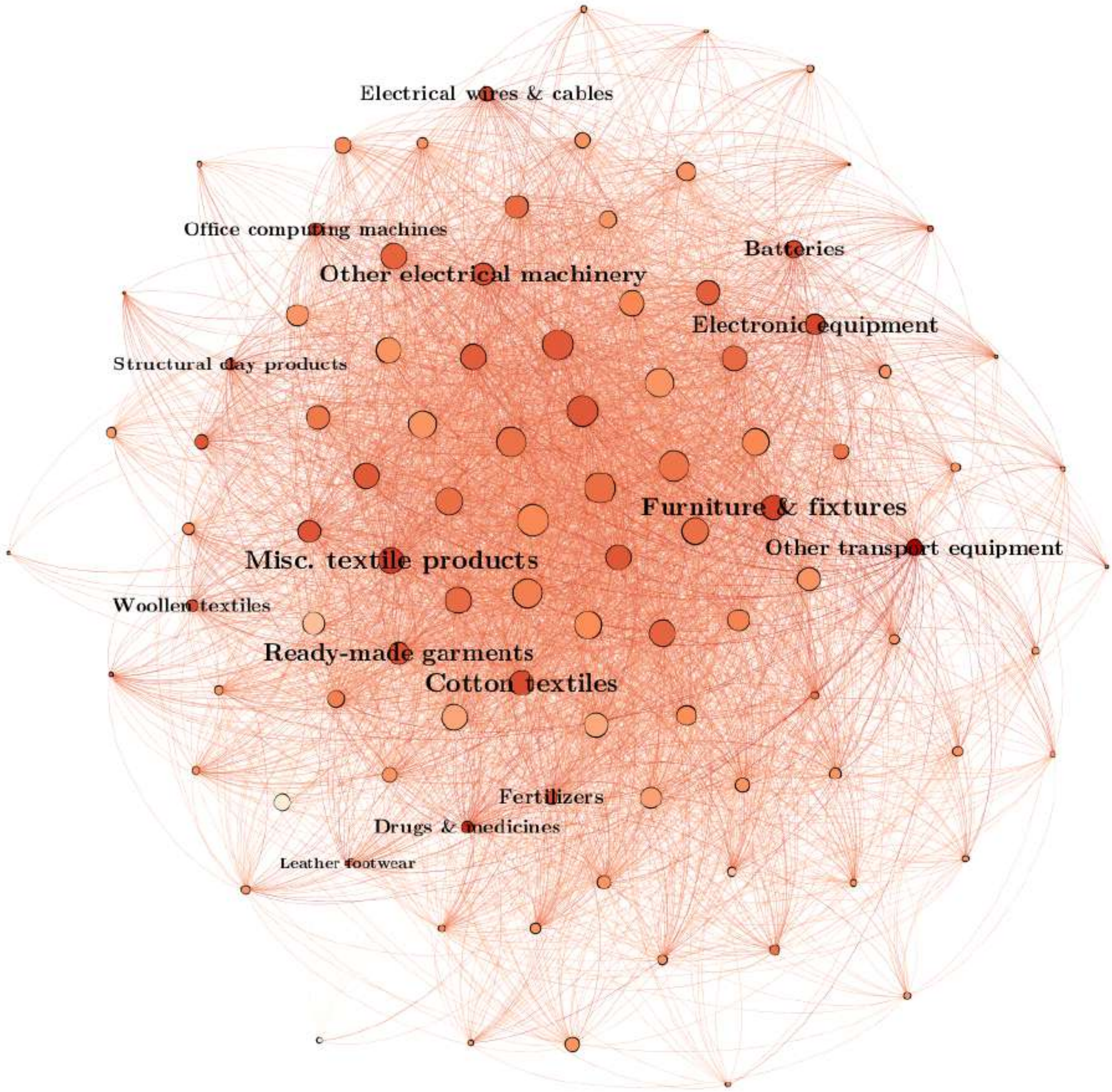


(b) Indian & Chinese exports to OECD



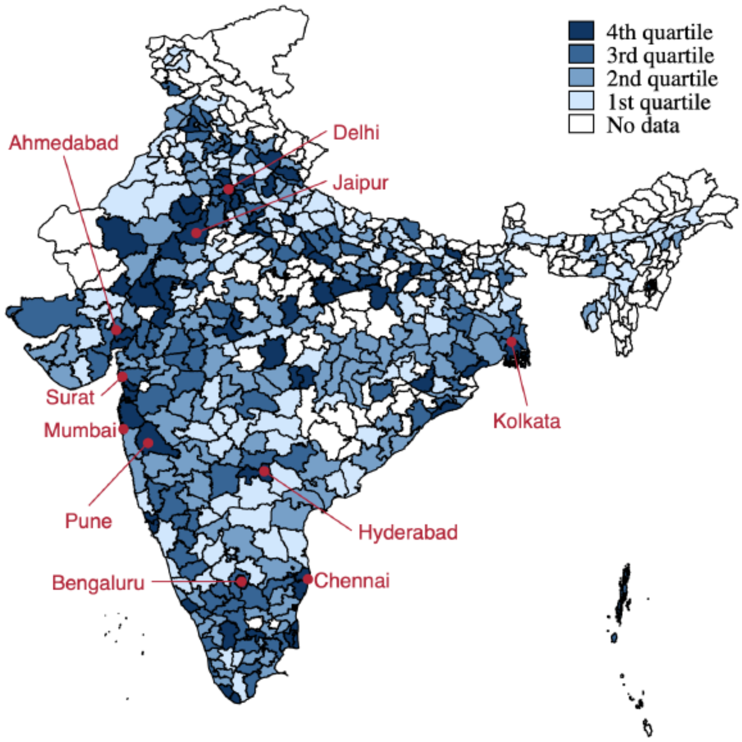
Notes: These graphs show total goods trade for four key relationships. Chinese imports into India have grown far faster than the reverse (highlighting channels (i)-(iii) from Figure 1.3 relative to channel (v)), while China has also greatly expanded its sales into the OECD market, where they compete with Indian exports (channel (iv)). *Source:* UN Comtrade.

Figure 3.2: Chinese import competition across the input-output network



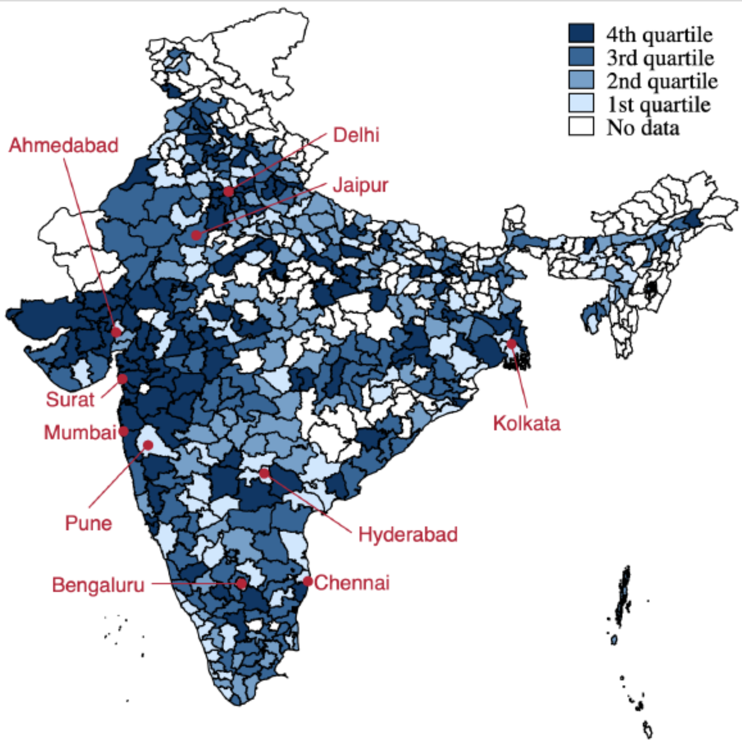
Notes: This graph shows the input-output connections between Indian primary and manufacturing industries in 1998. Nodes are scaled by number of downstream connections (out-degrees), and coloured darker the greater the increase in import competition between 1999 and 2013 – where import competition is measured by the share of Chinese imports in total Indian imports, as described in Section 5.2. Labels are shown for the top 15% of industries by increase in import competition.

Figure 3.3: Intensity of import competition among input industries by district



Notes: This map shows the change in the import competition faced by input industries between 2000 and 2008, by district, with darker shades reflecting larger increases. This measure is constructed as an average of the import competition faced by each input good, weighted by the value share of each in total input use, as in Section 5.2. The ten largest cities by population are labelled.

Figure 3.4: Quality upgrading by district



Notes: This map shows the change in the quality measure (described in Section 5.3) between 2000 and 2008, by district, with darker shades reflecting larger increases in quality. The ten largest cities by population are labelled.

4 Theory

This section outlines a simple model linking inputs and quality, then uses it to predict the impact of improved input supply, as well as the other four channels. The analysis focuses on firm behaviour in partial equilibrium for simplicity; it could also be extended to endogenise labour and input prices, but the results would not change qualitatively.

Consumers: Assume that consumers have constant elasticity of substitution (CES) preferences across horizontal varieties i. Define quality as the mean utility associated with consuming a product net of price (De Loecker et al. 2016), approximated by market share net of price following Berry (1994). Assume that vertical quality q_i enters multiplicatively with quantity x_i, such that a representative global consumer has utility:[19]

$$U = \left(\int_{i\in\Omega} (q_i x_i)^{\alpha} di \right)^{\frac{1}{\alpha}} \tag{4.1}$$

with elasticity of substitution $\sigma \equiv 1/(1-\alpha) > 1$ and $0 < \alpha < 1$. This gives demand $x_i = RP^{\sigma-1} q_i^{\sigma-1} p_i^{-\sigma}$ for product i, where R is total expenditure and $P = \left[\int_{i\in\Omega} \left(\frac{p_i}{q_i}\right)^{1-\sigma} di \right]^{\frac{1}{1-\sigma}}$ is a quality-adjusted ideal price index.

Note that the CES assumption is not critical for the conclusions of this paper. I adopt it for simplicity of exposition and because it matches the Khandelwal et al. (2013) method of deriving a quality measure. If deviations from CES lead to constant over- or under-estimation of the *levels* of quality and quality-adjusted prices, then this will not impact the conclusions of this paper on the *direction* of the impact of Chinese components on quality. Furthermore, one common concern with CES preferences, that they imply constant markups, is not severe in this context: Figure 4.1 Panel (a) shows only a weak relationship between quantity sold and markups, where markups are derived using the method of De Loecker et al. (2016), which requires only very general functional form assumptions. The major theoretical and empirical results of this paper are also robust to using linear demand, under which markups vary, as outlined in Appendix 9.

Firms: Let atomistic firms produce horizontally and vertically differentiated goods using (i) a numéraire labour input L with price $w = 1$, and (ii) raw materials with price m and

[19] This assumption of CES preferences with multiplicative quality is shared with other papers considering the interaction of inputs and quality, e.g. Kugler & Verhoogen (2012).

quality q_m. Let firms draw two independent and identically distributed parameters taking values between zero and infinity: firm-wide ability ϕ_f and firm-product-specific expertise λ_{fi}. These determine marginal costs $c_{fi} = \phi_f \lambda_{fi} m$ and quality $q_{fi} = (\phi_f \lambda_{fi} q_m)^{\theta+1}$, where $\theta > -1$ is a parameter reflecting the potential for quality differentiation. This reduced-form cost and quality structure, following Manova & Yu (2017) and Baldwin & Harrigan (2011), is substantially simpler than models which endogenise the quality decision (e.g. Verhoogen 2008, Johnson 2012) while retaining the relevant qualitative predictions.[20] The assumed positive relationship between cost and quality is based on the previous literature (Verhoogen 2008, Kugler & Verhoogen 2012, Manova & Zhang 2012, Crozet et al. 2012, Iacovone & Javorcik 2010), and also matches the data, as shown in Figure 4.1 Panel (b) – where marginal costs are calculated using the method of De Loecker et al. (2016), which again requires few assumptions, and quality is calculated using the method of Khandelwal et al. (2013), described below.[21]

Assume also that firms must pay a fixed headquarter cost F_h to operate and a fixed management cost F_i for each active product line. Firms produce those products for which they have sufficient ability and expertise to earn profits π_i greater than F_i, choosing prices and output to maximise $\pi_i(\phi_f, \lambda_{fi}) = p_i(\phi_f, \lambda_{fi}) x_i(\phi_f, \lambda_{fi}) - x_i(\phi_f, \lambda_{fi}) \phi_f \lambda_{fi} m - F_i$ subject to demand x_i, giving:

$$\begin{array}{lll} \text{Price} & p_i(\phi_f, \lambda_{fi}) & = \dfrac{\phi_f \lambda_{fi} m}{\alpha} \\ \text{QAP}^{22} & a_i(\phi_f, \lambda_{fi}) & = \alpha^{-1} q_m^{-(\theta+1)} m (\phi_f \lambda_{fi})^{-\theta} \\ \text{Quantity} & x_i(\phi_f, \lambda_{fi}) & = \alpha^{\sigma} R P^{\sigma-1} q_m^{(\theta+1)(\sigma-1)} m^{-\sigma} (\phi_f \lambda_{fi})^{\theta(\sigma-1)-1} \\ \text{Revenue} & r_i(\phi_f, \lambda_{fi}) & = \alpha^{\sigma-1} R P^{\sigma-1} q_m^{(\theta+1)(\sigma-1)} m^{1-\sigma} (\phi_f \lambda_{fi})^{\theta(\sigma-1)} \\ \text{Mark-up} & \mu_i(\phi_f, \lambda_{fi}) & = \dfrac{1}{\alpha} \\ \text{Profit} & \pi_i(\phi_f, \lambda_{fi}) & = \dfrac{r_i(\phi_f, \lambda_{fi})}{\sigma} - F_i \end{array} \begin{array}{r} (4.2) \\ (4.3) \\ (4.4) \\ (4.5) \\ (4.6) \\ (4.7) \end{array}$$

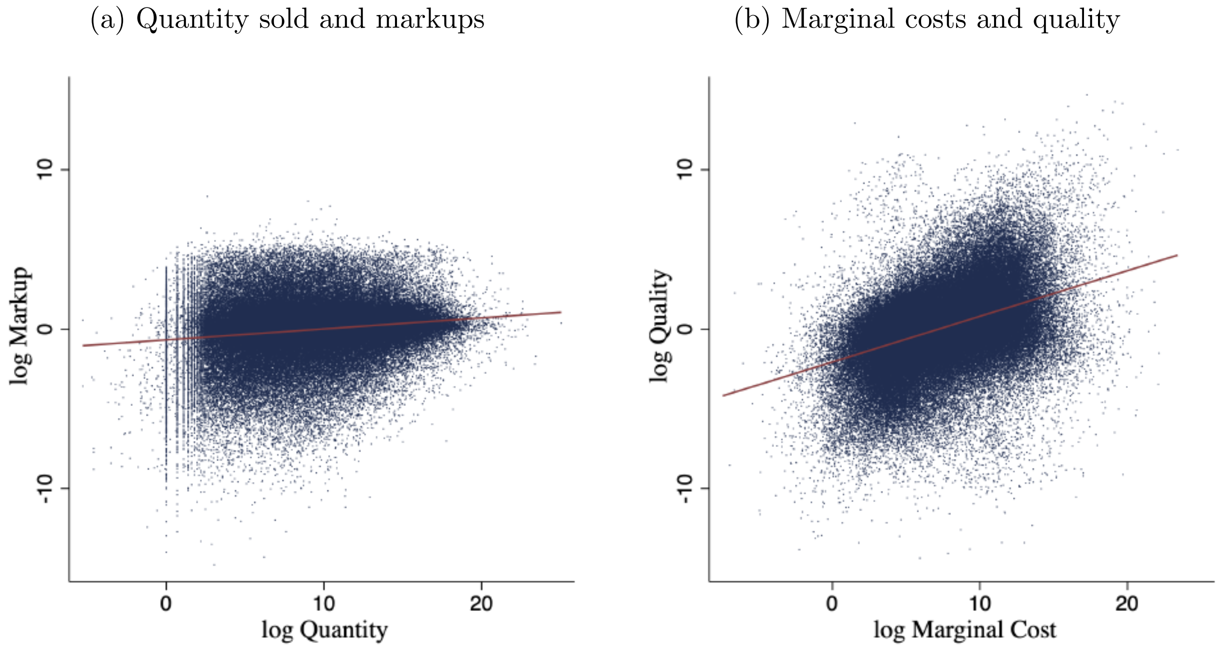
Cost- vs. quality-based competition: These results imply that firms engage in one of two types of competition, depending on the cost of producing higher quality goods. If $\theta \in (-1, 0)$,

[20] Following Manova & Yu (2017), the special case of $\theta = -1$ corresponds to the existing model of Bernard et al. (2010), while this case with linear demand (as outlined in Appendix 9), corresponds to Mayer et al. (2016).

[21] This framework also abstracts from within-firm product interdependencies in production or consumption, e.g. 'flexible manufacturing' and 'cannibalisation' effects (Eckel & Neary 2010). This substantially simplifies the model, yet does not affect the product hierarchy in quality or production efficiency (Manova & Yu 2017) so does not change the main qualitative predictions.

[22] QAP = quality-adjusted prices, i.e. price over quality.

Figure 4.1: Modelling assumptions and the data



Notes: These graphs show the observed empirical relationship between important variables in the model. Markups and marginal costs are derived using the method of De Loecker et al. (2016), which requires only very general functional form assumptions. Quality is calculated using the method of Khandelwal et al. (2013), described in Section 5.3 below. Markups are almost constant across firm size, supporting the use of CES preferences, while there is a strong positive relationship between cost and quality, as assumed in the model.

quality increases only slowly with costs, so firms with lower costs $\phi_f \lambda_{fi} m$ have higher revenue and profits – i.e. goods are relatively homogenous, so firms compete primarily on cost and price. In contrast, if $\theta > 0$ then quality increases faster than costs, so the higher prices received by firms with high ability ϕ_f and λ_{fi} outweigh the extra cost of producing high quality goods – i.e. when goods are relatively differentiated firms producing high quality goods have higher revenue and profits. This structure generates the testable propositions shown in Table 4.1.

Product scope: Firms produce those goods with $\pi_i > 0$, so the threshold expertise $\lambda^*(\phi_f)$ above which a firm will produce a good is defined by rearranging equation 4.7:

$$\lambda^*(\phi_f) = \phi_f^{-1} \left[\alpha^{1-\sigma} R^{-1} P^{1-\sigma} q_m^{(\theta+1)(1-\sigma)} m^{\sigma-1} \sigma F_i \right]^{\frac{1}{\theta(\sigma-1)}} \tag{4.8}$$

Thus the higher a firm's ability ϕ_f the lower the threshold and the larger the number of products N it will produce; noting the correlation between ability and costs c_i then gives Proposition 6 in Table 4.1.

Table 4.1: Observables for cost- vs. quality-based competition

Proposition		$\boldsymbol{\theta \in (-1, 0)}$		$\boldsymbol{\theta > 0}$
1. Price & Revenue across i within f:	$cov(p_i, r_i)$	< 0		> 0
2. Price & Revenue across f within i:	$cov(p_i, r_i)$	< 0		> 0
3. QAP & Revenue across i within f:	$cov(a_i, r_i)$	< 0	$\forall\, \theta > -1$	
4. QAP & Revenue across f within i:	$cov(a_i, r_i)$	< 0	$\forall\, \theta > -1$	
5. Quality & Cost across f within i:	$cov(q_i, c_i)$	> 0	$\forall\, \theta > -1$	
6. Scope & Cost across f within i:	$cov(N, c_i)$	> 0	$\forall\, \theta > -1$	

Notes: This table presents six propositions, derived from the model, which can be tested in the data. Each takes the form of a predicted covariance between two observable variables. In the first two cases, the expected relationship depends on the scope for quality differentiation, θ, unlike in the subsequent four. The propositions are tested in turn in Table 4.2.

Testing the framework: The regressions in Table 4.2 test each of the propositions of Table 4.1 in turn, and find strong correlational support for the key relationships predicted by the model. For instance, equations 4.2 and 4.5 imply that higher firm ability and expertise $\phi_f \lambda_{fi}$ correspond to (i) higher prices, and (ii) higher revenue the larger is θ. The first two columns in Table 4.2 test these predictions within and between firms, using the Rauch (1999) measure of product differentiability as a proxy for θ, and find strong support.[23] Columns (3)-(6) show similar tests for the remaining propositions, considering quality-adjusted prices, marginal costs, quality and firm scope.[24] This evidence is entirely correlation-based, and is not intended to prove that the highly stylised framework presented above is a perfect description of the Indian manufacturing sector. The aim is merely to show that the model has empirical relevance, sufficient to serve as a useful guide for thinking about the impact of the China shock on Indian manufacturing, as outlined in the following section.

Modelling the five channels: I now use this framework to model the impact of China's WTO accession on Indian manufacturing firms, through each of the five channels in Figure 1.3. First, model the improved access to new components as a reduction in quality-adjusted

[23]Specifically, I construct a 'homogenous' vs. 'differentiated' dummy as in Eckel et al. (2015), using Rauch's 'liberal' classification with his 'reference-priced' and 'traded on an organised exchange' categories amalgamated into the 'homogenous' category.

[24]Note that the corresponding propositions in Table 4.1 do not depend on θ, so I do not include an interaction with the Rauch measure.

Table 4.2: Tests of cost- vs. quality-based competition

	(1) PriceDM	(2) Price	(3) QAP	(4) QAP	(5) Quality	(6) Scope
Revenue	0.0973***	0.102***	-0.168***	-0.367***		
	(14.34)	(52.47)	(-49.88)	(-1847.89)		
Revenue × Dfftd	0.0323***	0.0151***				
	(2.78)	(4.36)				
Marginal cost					0.496***	0.0331***
					(101.57)	(6.72)
Fixed effects	ft	it	ft	it	it	it
Observations	61553	629999	432705	628359	149671	149675

Notes: t-statistics in parentheses. * p <0.10, ** p <0.05, *** p <0.01. Standard errors clustered at the firm level. All variables in logs, except *Dfft* and *Scope*. *Dfftd* = dummy variable for differentiated product, using Rauch (1999) liberal classification. *PriceDM* = de-meaned prices, to allow cross-product comparisons on price; quality-adjusted prices are already standardised during construction. Firm-time FEs remove variation across firms in the relationship being considered, leaving within-firm across-product variation; product-time FEs remove variation across products, leaving only within-product variation across firms. Marginal costs are calculated using the method of De Loecker et al. (2016), which requires only very limited functional form assumptions, and quality is calculated using the method of Khandelwal et al. (2013), as described in section 5.3. All regressions including a *Dfft* interaction also include *Dfft* alone as a control. All relationships are also robust to clustering at the product level or firm-product level rather than the firm level.

input prices caused by an improvement in input quality relative to input prices. Specifically, model increases in input quality Δq_m and input price Δm such that:

$$\frac{(\Delta q_m)^{\theta+1}}{\Delta m} > 1 \tag{4.9}$$

Under this condition, and when combined with equations 4.2 to 4.6, the firm responds by raising output quality more than prices, such that revenues rise even as quality-adjusted output prices fall. In other words, the improved access to components drives an increase in output quality, which is sufficiently attractive to consumers that revenues rise despite the downward pressure on demand from higher prices. The impact on the probability of product exit, Ex_i, then follows straightforwardly from profit in equation 4.7: higher product-wise revenue r_i raises the the probability of covering the product-specific fixed cost F_i, so lowers the probability that the firm drops the product. These impacts are shown in row (i) of Table 4.3, which summarises the predicted effects on variables which can be observed in or derived from the ASI data.[25]

[25] The impact on output quantity x_i of improved access to inputs is not shown, as (a) it is not critical for the argument of this paper, and (b) the direction of the effect is not determined by the minimal assumption

The impacts on firms through the other remaining channels – shown in rows (ii) to (v) of Table 4.3 – follow similarly. Firstly, model direct import competition with Good 0 as an expansion in the set of varieties Ω available, which reduces residual demand, quantity and revenue for each good i via a fall in the price index term $P^{\sigma-1}$ in equations 4.4 and 4.5. Second, model import competition via outputs as a reduction in expenditure R – the 'consumers' of Good 0, namely those firms to which it is sold as a component, reduce their scale of input purchases in response to import competition for their product (Good 1 in Figure 1.3).[26] Third, model increased export competition in the same way as direct import competition – the forces are the same, merely occurring in export markets rather than the domestic market.[27] Lastly, model the increased demand from improved access to Chinese consumers as a rise in total consumer expenditure R, which raises quantity and revenue.

With these predictions in hand, I next turn back to the data and outline methods for testing them. Appendix 9 derives equivalent predictions for the case of linear demand – all predictions remain qualitatively the same, except for some new price effects resulting from the concomitant variation in markups.

Table 4.3: Predicted impacts of the China shock on observables

		Channel	***Shock***	$\boldsymbol{c_i}$	$\boldsymbol{q_i}$	$\boldsymbol{p_i}$	$\boldsymbol{a_i}$	$\boldsymbol{x_i}$	$\boldsymbol{r_i}$	$\boldsymbol{Ex_i}$
Import Competition:	(i)	via Inputs	$\uparrow q_m > \uparrow m$	↑	↑	↑	↓	~	↑	↓
	(ii)	Direct	$\uparrow \Omega \rightarrow \downarrow P^{1-\sigma}$	–	–	–	–	↓	↓	↑
	(iii)	via Outputs	$\downarrow R$	–	–	–	–	↓	↓	↑
Exports:	(iv)	Competition	$\uparrow \Omega \rightarrow \downarrow P^{1-\sigma}$	–	–	–	–	↓	↓	↑
	(v)	Opportunity	$\uparrow R$	–	–	–	–	↑	↑	↓

Notes: This table summarises, for each channel, the predicted effects on variables which can be observed in or derived from the ASI data. From left to right, the outcome variables are: c_i – marginal cost; q_i – quality; p_i – price; a_i – quality-adjusted price; x_i – quantity; r_i – revenue; Ex_i – probability of dropping the product next period.

on the relative sizes of the input quality and input price rises specified in equation 4.9.

[26] I model these 'customer' firms as consumers for simplicity, to avoid requiring an extra layer of firms in the model. The model could be extended in this way, but the qualitative predictions in Table 4.3 would be unchanged.

[27] While the expected impacts on observables have the same pattern, these channels can still be identified independently as they are driven by variation in different bilateral tariffs and different import/export flows.

5 Empirics

In this section, I outline two complementary methods for identifying effects through the five channels, respectively using data on tariffs and imports/exports (hereafter 'flows'). The tariff method exploits China's 2001 accession to the WTO, while the flow method builds on Autor, Dorn & Hanson (2013) to isolate plausibly exogenous variation in Indian imports from, and exports to, China. Intuitively, fundamental changes in tariff regimes should have real effects in import and export flows, so I draw on both methods in the main results. I close the section with an overview of the outcome variables used in the analysis.

5.1 Tariff method

First, I measure each of the channels by changes in the relevant bilateral tariffs. The extent of direct import competition faced by Indian firms (channel (ii) in Figure 1.3) is directly related to the level of Indian tariffs on Chinese goods. Denote the annual tariffs on these flows from China into India as $CITariff_{it}$, where i is a five-digit CPC product code. I can then measure the input channel as a weighted average of the tariffs on each input used by firms:

$$InputTariff_{it} = \sum_k \alpha_{ik} \cdot CITariff_{kt} \tag{5.1}$$

where $\alpha_{ik} = \frac{Sales_{ki}}{\sum_k Sales_{ki}}$ is the value share of input k in total input use by producers of i, calculated using the 1998 input-output table compiled by MoSPI.[28] To avoid double-counting the direct import competition channel, I set α_{ii} to zero for all i. Similarly, I measure import competition effects through the output channel using a weighted average of the tariffs on those final goods that use a given input:

$$OutputTariff_{it} = \sum_k \gamma_{ik} \cdot CITariff_{kt} \tag{5.2}$$

where $\gamma_{ik} = \frac{Sales_{ik}}{\sum_k Sales_{ik} + FinalDemand_i}$ is the share of total usage of input i that is for production of k, again calculated using the 1998 input-output table and with γ_{ii} set to zero for all i.

I then measure export effects in a similar manner to direct import competition. Export competition (channel (iv) in Figure 1.3) relates to China's access to major export markets, and

[28] I use the 1998 input-output table in every year throughout the period to prevent potential endogeneity of the input-output structure with respect to tariff levels and/or trade flows. Results are also robust to using the less granular IOT from the OECD Structural Analysis Database.

hence to the level of tariffs imposed by third countries on Chinese goods. I approximate this with $CRTariff_{it}$, the average of US, EU and Japanese tariffs on Chinese goods – destinations which together account for at least 25% of Chinese exports in every year in the sample. Lastly, I use the level of tariffs faced by Indian exports into China, $ICTariff_{it}$, to gauge the export opportunity channel.

The changes over time in the median levels of the three core tariff measures are shown in Figure 5.1 Panel (a).[29] Following China's accession to the WTO in 2001, there is a rapid reduction in bilateral tariffs between India and China, then a subsequent stabilisation around the new lower level. This motivates a difference-in-differences approach, comparing products facing high and low initial tariff levels in the periods before and after China's accession to the WTO. Building on Lu & Yu (2015), I therefore run:

$$\begin{aligned}
\ln y_{ift} = {} & \alpha_{(i)} \cdot Post2001_t \cdot \ln InputTariff_{i,2001} \\
& + \alpha_{(ii)} \cdot Post2001_t \cdot \ln CITariff_{i,2001} \\
& + \alpha_{(iii)} \cdot Post2001_t \cdot \ln OutputTariff_{i,2001} \\
& + \alpha_{(iv)} \cdot Post2001_t \cdot \ln CRTariff_{i,2001} \\
& + \alpha_{(v)} \cdot Post2001_t \cdot \ln ICTariff_{i,2001} \\
& + \boldsymbol{\alpha}'\mathbf{X}_{ft} + a_i + b_f + c_{st} + u_{ift}
\end{aligned} \tag{5.3}$$

where $Post2001_t$ is a dummy taking value one after 2001, and $\mathbf{X}_{ft}$ contains a vector of firm-time controls, specifically whether a plant is in a rural or urban area and whether it is privately owned, publicly owned or a mixture. Outcomes y_{ift} are at the firm-product-time level, and I include product, firm and state-time fixed effects.[30] Standard errors are clustered at the firm level to account for potential correlation in supply and demand shocks within firms over time.[31]

The estimated coefficient for each channel reflects the percentage impact on the outcome variable in the post-2001 period of having a tariff one percent higher prior to China's accession (and thus a larger fall in tariffs post-accession). I use only pre-accession tariffs, rather than annual tariffs, because the planned schedule of tariff reductions was released in 2002, so subsequent changes in tariffs were expected and hence could be pre-empted by producers (Lu

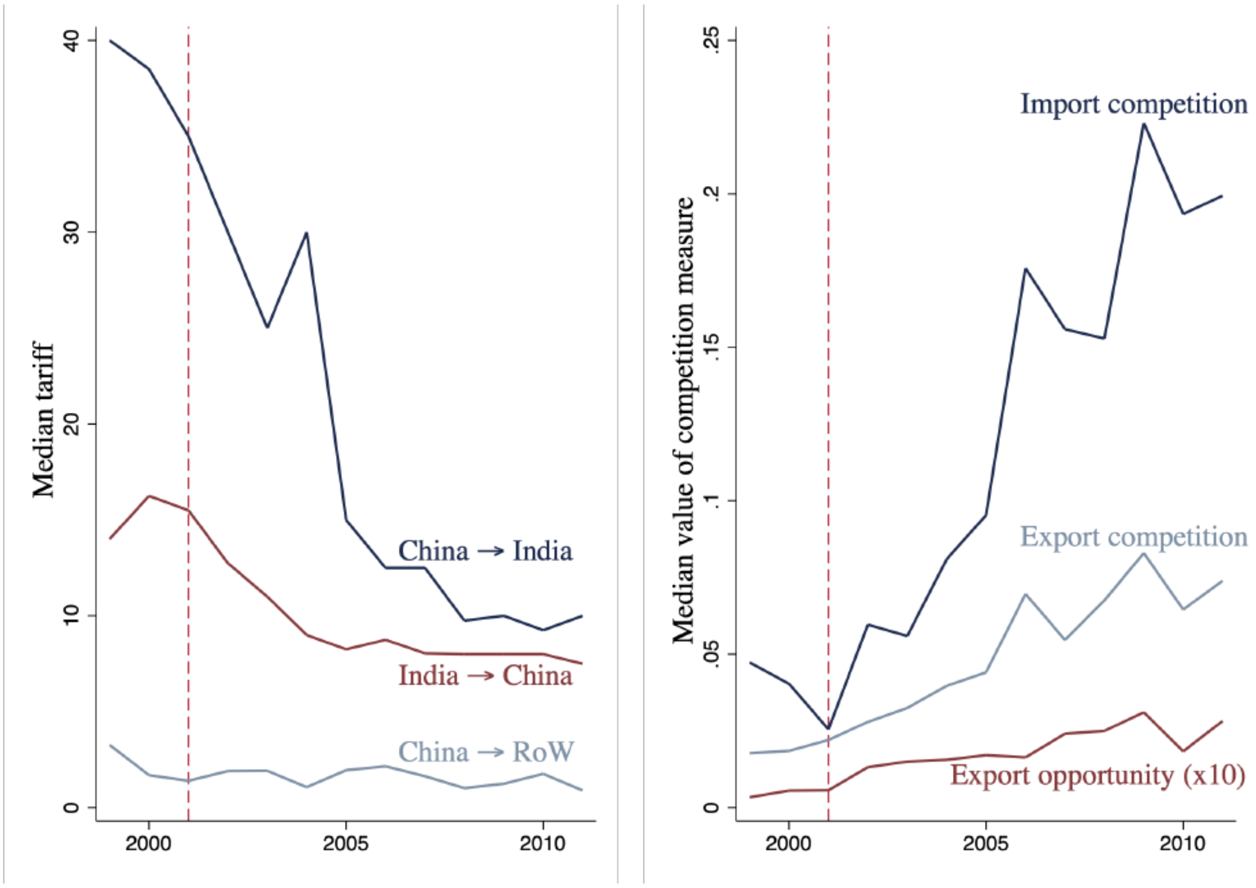
[29]The input and output measures are not shown, as these are simply weighted combinations of 'China $\rightarrow$ India' variation.

[30]I describe the specific outcome variables used in Section 5.3 below.

[31]For instance, firms with strong management may be more likely to maintain high quality standards through an interval of slow growth. Results are also robust to clustering at the product-level.

Figure 5.1: Changes in tariffs and trade flow measures, by channel

(a) Tariffs (b) Flows



Notes: These graphs show the trends in the median values of the tariff and flow measures, as described in Sections 5.1 & 5.2 respectively. As noted in the text, the two other channels (input and output effects, i.e. (i) and (iii) in Figure 1.3) are simply weighted averages of the direct import competition channel (shown in dark blue in both graphs). The values of the export opportunity channel in Panel (b) are magnified by a factor of ten, so that the trend is visible despite the very low share of Indian goods in total Chinese imports.

& Yu 2015). In contrast, the exact timing of China's accession to the WTO was not clear until 2001, as many important issues were not resolved until mid-2001 – for instance, Mexico held off on agreeing terms until September 2001, with the final accession agreement then following two months later (Lu & Yu 2015).[32]

The key identifying assumption is that outcomes in firms facing large falls in tariffs after 2001 would have followed the same path as in firms facing small falls, if there had been no

[32]Nonetheless, the results are robust to using a specification based on annual tariffs, as in Brandt et al. (2017).

trade liberalisation in 2001, conditional on the controls. Specifically, I require:[33]

$$\begin{aligned}
& E\big[u_{ift} | Post2001_t \cdot \ln InputTariff_{i,2001}, \\
& \qquad Post2001_t \cdot \ln CITariff_{i,2001}, \\
& \qquad Post2001_t \cdot \ln OutputTariff_{i,2001}, \\
& \qquad Post2001_t \cdot \ln CRTariff_{i,2001}, \\
& \qquad Post2001_t \cdot \ln ICTariff_{i,2001}, \\
& \qquad \mathbf{X}_{ft}, a_i, b_f, c_{st}\big] \\
= \; & E\big[u_{ift} | \mathbf{X}_{ft}, a_i, b_f, c_{st}\big]
\end{aligned}$$

The first major endogeneity concern is reverse causality. For instance, Indian tariffs could be lowered only for those industries where Chinese imports are least threatening, namely those with strong domestic sales or quality growth. The second major concern is misattribution, i.e. the existence of a third set of factors correlated with tariff cuts which also affect firm outcomes. Political influence is an archetypal case (e.g. Grossman & Helpman 1994); industries with lobbying power could ensure protective tariffs, along with preferential access to subsidies or other support for their firms.

Both these concerns are ameliorated by inspecting the tariff reductions. Figure 5.2 plots baseline tariffs, and the subsequent changes, for each of the channels. Consider initially the top four graphs, accounting for channels (i)-(iii) and (v). While there is wide dispersion in tariff levels in 1996, the subsequent changes align very closely with the grey reference line, with gradient -1. In other words, tariffs that are one percentage point higher in 1996 tend to fall by one percentage point more by 2011: tariffs converge tightly onto the low and relatively uniform WTO rates.[34] The initial phase of this convergence is clear in the righthand graphs, which show less horizontal dispersion in 2001 tariff levels (as well as remaining close to the 1:1 perfect convergence line). By the end of the period there is little remaining variation, so there is limited scope for tariffs to have been selectively lowered for some industries relative

[33]Note with Lu & Yu (2015) that exogeneity of the control variables is not necessary for identification of the coefficients of interest; i.e. I do not require

$$E\big[u_{ift} | \mathbf{X}_{ft}, a_i, b_f, c_{st}\big] = 0$$

which would allow a causal interpretation of the coefficients on the control variables also (Stock & Watson 2014).

[34]I use 2011 as the end year because it is the last year in my sample for which TRAINS tariff data is available for all three channels. The patterns remain very similar when using different endpoints across 2012-2014, where available.

to others.

With regard to misattribution, this tight convergence implies that there cannot be factors which caused both a large fall in tariffs and better firm performance, unless they were also present before 1996. Given that my fixed effects account for firm and industry characteristics, it is unlikely that such factors affect my results. Nonetheless, in robustness checks in Appendix 10.B, I take the additional precaution of controlling explicitly for various possible confounding factors, such as lobbying efforts or industrial strategy towards infant industries.

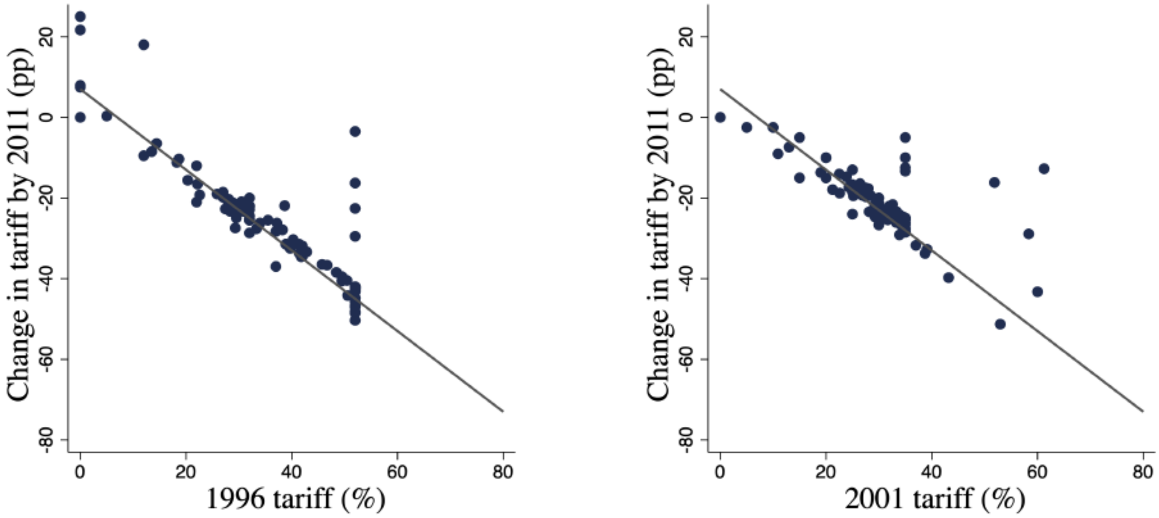
A similar argument alleviates reverse causality concerns. For strong firm performance in the 2000s to cause a larger fall in some tariffs, it would effectively have to determine tariffs as far back as 1996, given that subsequent changes are driven predominantly by convergence. This is implausible given the highly unpredictable nature of the rapid economic changes unleashed after China's WTO accession.[35]

Turning to the bottom two graphs of Figure 5.2, reflecting export competition, the picture is very different. There is substantially less variation in tariffs, and no clear fall in tariffs after 2001 – tariffs are already at a fairly uniform low rate. This reflects the fact that China's main trade partners negotiated lower bilateral tariffs with China *before* 2001, whether on a 'Permanent Normal Trade Relations' basis (as in the EU from the 1980s), or in the form of annual renewals of NTR status (as in the USA until 2001, when China's new PNTR status became effective on its accession to the WTO). The key change in 2001 was thus the reduction in trade uncertainty, which allowed increased investment in production of exports, rather than a change in tariff levels *per se* (Pierce & Schott 2016).

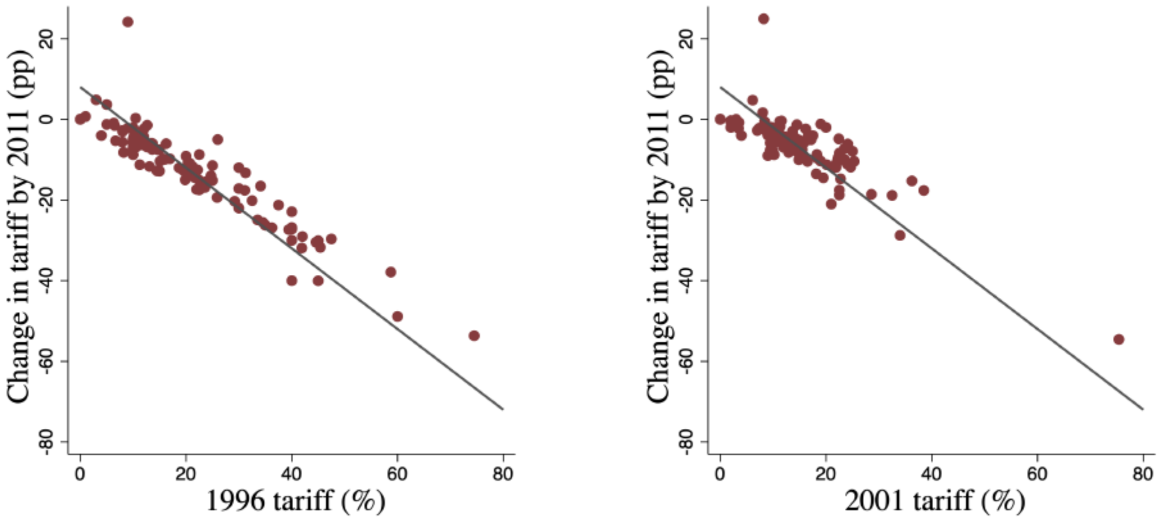
To check that this export competition channel is not affecting my results on the impact of Chinese components, and to address any remaining endogeneity concerns, I therefore complement the tariff regressions with an alternative identification method. This uses import/export flows, building on Autor et al. (2013), and so picks up variation through all of the channels, as seen in Figure 5.1 Panel (b). I outline this method in the next section.

[35]For instance, the dramatic expansion in Chinese import competition in India was not widely predicted even by the early 2000s. One study in the *Economic and Political Weekly* concluded: "Bilateral trade ... is quite limited, with India's exports [to China] constituting about 2 per cent of its exports and India's imports from China constituting about 3 per cent of total imports in 2000-01. ... Thus, given the limited bilateral trade with China, it is unlikely there will be a significant impact of China's entry into WTO on India's imports" (Agrawal & Sahoo 2003). By 2010, Chinese products made up more than 25% of total Indian imports.

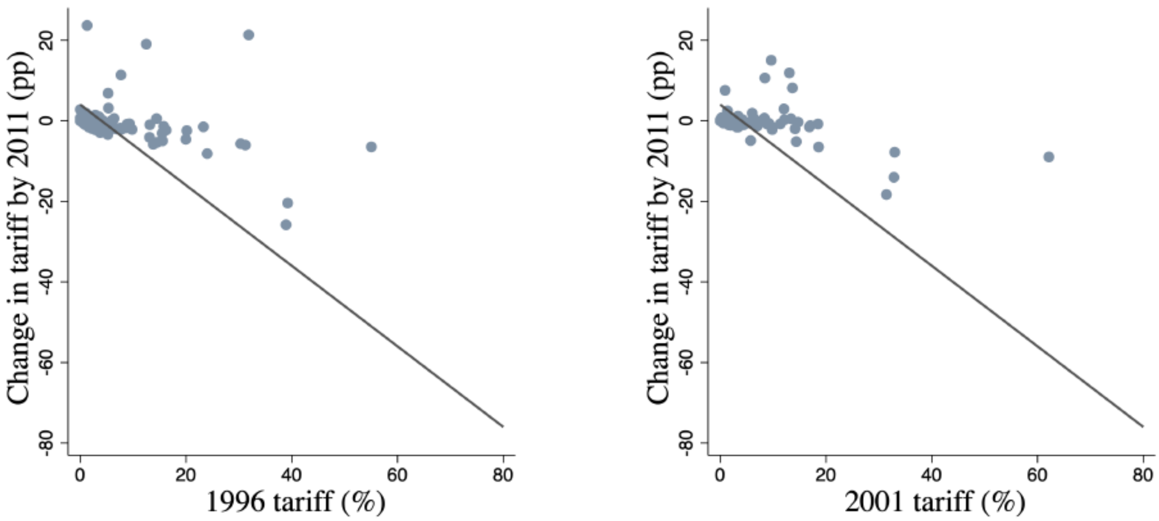
Figure 5.2: Inspecting the tariff changes



(i,ii,iii) Import competition



(v) Export opportunity



(iv) Export competition

Notes: These graphs plot the change in tariffs by 2011 against their initial levels in 1996 and 2001, for three-digit CPC industries. The grey reference line has a gradient of -1 for comparison.

5.2 Flow method

Intuitively, if the tariff changes outlined above have real effects, then these will be directly observable in import and export flows. I therefore construct analogous measures of the five channels using data on trade flows. Direct import competition can be measured, following Schott (2002), by China's share of total Indian imports, i.e.

$$CIFlow_{it} = \frac{M^{China}_{India,it}}{M^{World}_{India,it}} \tag{5.4}$$

where $M^{China}_{India,it}$ is Indian imports from China of product i in year t, and likewise $M^{World}_{India,it}$ is total Indian imports of i from the World.[36] The input channel is then a weighted average of this import competition, across inputs k used in production of good i, as in equation 5.1 in the previous section:

$$InputFlow_{it} = \sum_k \alpha_{ik} \cdot \frac{M^{China}_{India,it}}{M^{World}_{India,it}} \tag{5.5}$$

Intuitively, this reflects the extent to which Chinese components are entering the markets for a good's inputs. The third channel, output effects of input competition, follows in the same way:

$$OutputFlow_{it} = \sum_k \gamma_{ik} \cdot \frac{M^{China}_{India,it}}{M^{World}_{India,it}} \tag{5.6}$$

Similar to equation 5.2 in the previous section, this reflects the extent to which the products k using good i as an input are facing import competition from China (which could then spill upstream to reduce demand for good i itself).

I measure the final two channels analogously. My export competition measure is essentially the same as the import competition variable, except applied to OECD export destinations rather than the Indian market:

$$CRFlow_{it} = \frac{M^{China}_{OECD,it}}{M^{World}_{OECD,it}} \tag{5.7}$$

In other words, I use China's share of total OECD imports to proxy for Chinese competitive pressure on India's export markets.[37] Lastly, I measure the export opportunity channel by

[36] I follow Schott (2002), Bernard & Jensen (2002) and Barua (2016) in using this value share measure of import competition rather than the import penetration rate (i.e. imports over domestic production plus imports) or import price measures due to the lack of availability of comprehensive product-level domestic production data or import price time series.

[37] I use exports to the OECD, rather than to the whole world, to avoid any overlap between the set of export markets considered and the countries used in the instrument discussed below. Exports to the OECD

the inverse of the import competition channel, i.e. by India's share in total Chinese imports:

$$ICFlow_{it} = \frac{M^{India}_{China,it}}{M^{World}_{China,it}} \tag{5.8}$$

Thus all five variables have the same structure – specifically, a share (or weighted average of shares) of the total imports of some country or group of countries.

The trends in the underlying variables are shown in Panel (b) of Figure 5.1. Import competition, export competition and export opportunity all rise substantially over the period, and particularly after 2001. In the graph, I multiply the values of the latter by ten so that the trend is visible – the export opportunity channel is by far the smallest of the three, reflecting the very small share of Indian products in China's imports.[38]

The next step is to identify exogenous variation in these measures, so I can examine their effects on firm outcomes. All except $CRFlow_{it}$ include either Indian imports or Indian exports, and so may reflect not just the exogenous supply-side shock from China's integration but also Indian supply-side or demand-side shocks. I therefore construct instrumental variables in the manner of Autor et al. (2013), replacing the India-related terms with alternatives constructed from a basket C of comparable Southeast Asian countries (Bangladesh, Indonesia, Malaysia, Philippines, Thailand).[39] Specifically, I construct:

$$CIFlow^{IV}_{it} = \frac{\sum_{c \in C} M^{China}_{c,it}}{\sum_{c \in C} M^{World}_{c,it}} \tag{5.9}$$

$$InputFlow^{IV}_{it} = \sum_k \alpha_{ik} \cdot \left[\frac{\sum_{c \in C} M^{China}_{c,kt}}{\sum_{c \in C} M^{World}_{c,kt}} \right] \tag{5.10}$$

$$OutputFlow^{IV}_{it} = \sum_k \gamma_{ik} \cdot \left[\frac{\sum_{c \in C} M^{China}_{c,kt}}{\sum_{c \in C} M^{World}_{c,kt}} \right] \tag{5.11}$$

$$ICFlow^{IV}_{it} = \frac{\sum_{c \in C} M^{c}_{China,it}}{M^{World}_{China,it}} \tag{5.12}$$

In short, I instrument for Chinese import competition in India with import competition in the comparison countries, and I instrument for Indian export opportunities in China with the comparison countries' export opportunities in China.

are a large share of India's total exports; e.g. 22.6% of total exports in 1999 were to the USA alone, while the largest non-OECD market was Hong Kong at 6.1%.

[38] As well as having a substantial trade deficit with China, shown in Figure 3.1, total Chinese imports are far larger than total Indian imports (e.g. $460 billion vs. $93 billion in 2004).

[39] I choose these economies because they all (a) have a similar degree of diversification to India, and/or similar GDP per capita to India at the start of the period studied, and (b) have Comtrade data available throughout the period.

I use these measures to run an alternative, complementary specification, which can exploit annual variation because China's WTO accession is no longer required for identification. Specifically, I run:

$$\begin{aligned}\ln y_{ift} = {} & \alpha_{(i)} \cdot \ln InputFlow_{it} \\ & + \alpha_{(ii)} \cdot \ln CIFlow_{it} \\ & + \alpha_{(iii)} \cdot \ln OutputFlow_{it} \\ & + \alpha_{(iv)} \cdot \ln CRFlow_{it} \\ & + \alpha_{(v)} \cdot \ln ICFlow_{it} \\ & + \boldsymbol{\alpha}'\mathbf{X}_{ft} + a_i + b_f + c_{st} + u_{ift}\end{aligned} \tag{5.13}$$

where $InputFlow_{it}^{IV}$, $CIFlow_{it}^{IV}$, $OutputFlow_{it}^{IV}$ and $ICFlow_{it}^{IV}$ are used to instrument for channels (i)-(iii) and (v) respectively.

5.3 Outcome variables

As modelled above, improved access to components affects several firm-product-level outcomes. I can observe any impacts on prices, quantities and sales directly in the ASI data. Building on Khandelwal et al. (2013), I can also use these to derive a measure of quality: intuitively, for a given utility function, if one product sells more units than another at the same price, this suggests that it is higher quality. Begin with the utility function previously assumed in equation 4.1 in the theory section.[40] As noted above, demand x_i for product i is:

$$x_i = RP^{\sigma-1} q_i^{\sigma-1} p_i^{-\sigma} \tag{5.14}$$

for expenditure R and price index P, where q_i is quality. Taking logs and moving prices to the left-hand side gives:

$$\ln x_i + \sigma \ln p_i = \ln R + (\sigma-1)\ln P + (\sigma-1)\ln q_i \tag{5.15}$$

[40] Note that the narrow assumptions of a single representative consumer and a single vertical dimension of quality can also be justified in a model with many individual consumers making discrete choices, as shown by Anderson et al. (1992): quality is interpreted as a component of product attributes that all consumers value, assuming only that the residuals of consumers' heterogeneous valuations have mean zero.

Noting that quantity, quality and price vary with firm f over time t, and that expenditure R and price level P vary over time, this can be re-written as:

$$\begin{aligned}\ln x_{ift} + \sigma \ln p_{ift} &= \ln R_t + (\sigma - 1)\ln P_t + (\sigma - 1)\ln q_{ift} \\ &= \alpha_t + u_{ift} \end{aligned} \tag{5.16}$$

Adding an extra product fixed effect to account for differing units of price or quantity across products gives:

$$\ln x_{ift} + \sigma \ln p_{ift} = \alpha_t + \alpha_i + u_{ift} \tag{5.17}$$

Thus for a given value of σ, quality $\ln \hat{q}_{ift} = \frac{\hat{u}_{ift}}{\sigma - 1}$ can be estimated as the residual in a regression of observable prices and quantities on a time and a product fixed effect.[41] Prices are effectively partialled out, leaving 'quantity conditional on price', i.e. quality. Quality-adjusted prices are then given by:

$$\ln \widehat{a}_{ift} = \ln p_{ift} - \ln \hat{q}_{ift} \tag{5.18}$$

Of the seven outcome variables in Table 4.3, this leaves just marginal costs and revenue to be explained. I estimate the former using the algorithm of De Loecker et al. (2016), which first backs out markups from observable firm-product variables, then combines these with observed prices to compute marginal costs. The procedure allows for very flexible functional forms, so does not clash with the assumptions required for the Khandelwal et al. (2013) quality-estimation method.

Finally, I measure product exit by observing whether a firm-product appears in the next year of the sample. Specifically, I follow Iacovone et al. (2013) in defining:

$$Ex_{ift} = \begin{cases} 1 & \text{in the last year that firm-product } if \text{ is observed in the sample} \\ 0 & \text{otherwise} \end{cases}$$

where the last year of the sample is dropped, as in that year it is not possible to measure Ex_{ift}. I focus on firms in the ASI census panel to allow exit to be measured, but also use the representative survey sample in robustness checks.[42] I do not log Ex_{ift} when including it in specifications 5.3 and 5.13 above, since it has mostly zero values. Thus each estimated

[41] This paper uses $\sigma = 3.7$, the median estimated elasticity of substitution for India calculated by Broda, Greenfield & Weinstein (2006), as discussed in Section 10.A.

[42] I investigate the impact of selection out of the census panel on firm-product exit in Appendix 10.E, and find no material impact on the results.

α is the coefficient in a linear probability model – representing the marginal change in the probability of product exit resulting from the relevant tariffs being one percent higher in 2001.

6 Results: Baseline

My baseline specification uses the tariff method to investigate each of the relationships in row (i) of Table 4.3 – i.e. to test the theoretical predictions of the impact of improved access to Chinese components. Table 6.1 Panel A shows the impact, through the input channel, on marginal costs, quality, price, quality-adjusted prices, quantity, revenue and the probability of dropping a product. The specification follows equation 5.3, controlling for the other four channels, rural/urban location, public/private ownership, and product, firm and state-time fixed effects. Each coefficient represents the percentage impact in the post-2001 period of input tariffs being one percent higher in 2001 – and so falling by approximately that much more subsequently, as seen in Section 5.1.[43]

The results match the predictions of the model. Consistent with higher quality inputs, there is a significant rise in output quality. Consistent with the assumption in equation 4.9 that the rise in input quality outweighs the rise in their raw prices, quality-adjusted prices fall even as marginal costs and prices rise. Higher quality at lower quality-adjusted prices drives a rise in revenue, which increases product-wise profit and so reduces the probability of a product being dropped.[44]

Taken together, these results suggest that both firms and consumers benefit from improved access to Chinese components. Firms increase revenue and reduce product dropping – which is correlated with profit in a wide class of models, including the CES and linear demand setups used in this paper. Consumers experience a net gain *qua consumers*, i.e. in their role as goods-consuming agents: they receive higher quality products at lower quality-adjusted prices. The question of whether consumers gain in an 'all things considered' sense is beyond the scope of this paper and would require further assumptions on the structure of the labour market and the distribution of consumers' consumption bundles. Here I simply note (i) the robust finding that firms producing higher quality goods pay higher wages to their workers (e.g. Verhoogen 2008, Kugler & Verhoogen 2012), which suggests that consumers could also benefit from quality upgrading in their roles as workers, and (ii) the link between quality

[43]The exit variable has a slightly different interpretation, as it is binary and so not logged: each coefficient represents the *marginal* change in the probability of dropping the product, as described in Section 5.3.

[44]The minimal assumptions underlying the predictions in Table 4.3 do not imply a specific impact on quantity, and indeed I observe no significant effects in the quantity regressions.

upgrading and development, which suggests that quality upgrading may also benefit them through long-run growth.[45]

Table 6.1: Input effects of China's WTO accession

	MCs	Quality	Price	QAP	Quantity	Revenue	Exit
Panel A: Full Sample							
$InputTariff$	0.298**	0.238***	0.194***	-0.0421***	-0.0821	0.0704**	-0.0180*
	(2.57)	(4.27)	(3.72)	(-2.84)	(-1.32)	(2.13)	(-1.95)
FEs	i,f,st	i,f,st	i,f,st	i,f,st	i,f,st	i,f,st	i,f,st
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	34408	165011	165579	165011	165017	175799	161072
Panel B: Intensive Margin Only							
$InputTariff$	0.310***	0.243***	0.199***	-0.0405***	-0.0928	0.0671**	-0.0163*
	(2.62)	(4.35)	(3.80)	(-2.72)	(-1.48)	(2.06)	(-1.73)
FEs	i,f,st	i,f,st	i,f,st	i,f,st	i,f,st	i,f,st	i,f,st
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	28460	137780	138229	137780	137785	147843	139739

Notes: t-statistics in parentheses. * p <0.10, ** p <0.05, *** p <0.01. Standard errors clustered at the firm level. All variables in logs, except *Exit* which is as described in Section 5.3. Panel A includes all products, while Panel B only includes those products which first appear in the dataset prior to China's WTO accession at the end of 2001. All regressions include firm, product and state-year FEs, and control for rural/urban location, public/private ownership, and the other four channels (import competition, export opportunity, export competition and upstream spillovers). Quality and quality-adjusted prices are calculated using the procedure of Khandelwal et al. (2013), and marginal costs are calculated using the procedure of De Loecker et al. (2016). The input channel is measured as described in Section 5.1 – i.e. each coefficient gives the percentage change in the average value of the outcome variable in the post-accession period resulting from a 1% higher average pre-accession tariff on the firm's inputs.

These results relate closely to the work of Goldberg, Khandelwal, Pavcnik & Topalova (2010*a*), who consider the liberalisation of Indian tariffs in the early 1990s. They find that access to new intermediate inputs causes a substantial expansion in the range of goods produced by manufacturers, a 'variety in, variety out' result echoed by my 'quality in, quality out' mechanism. However, in the ASI data less than 20% of goods produced after 2001 are new products (at the seven-digit level), and the quality-upgrading effect holds strongly even when excluding new products from the sample, as in Table 6.1 Panel B. By the end of the 1990s Indian manufacturing had liberalised substantially, as documented extensively by Goldberg and coauthors. My findings therefore suggest that many of the initial extensive margin gains from liberalisation had played out by 2001, such that the primary benefit to India of China's WTO accession came through the intensive margin, specifically through quality upgrading of existing products.

[45]On (ii), see, for instance, Grossman & Helpman (1991), Kremer (1993), Hausmann & Rodrik (2003), Rodrik (2006), Hidalgo et al. (2007), Matsuyama (2008), Khandelwal (2010), Lane (2019), Verhoogen (2020).

Robustness: Table 6.2 tests the robustness of this 'supply-driven quality upgrading' story. The first two columns add two-digit sector-time fixed effects to account for broad industry trends, which would affect the above conclusions if, for instance, 2001 tariffs were systematically higher in sectors with faster average growth in quality. The next two columns use the alternative identification method from Autor, Dorn & Hanson (2013), as described in Section 5.2. Lastly, columns five and six test for upgrading using an alternative measure, firm-level total factor productivity (TFP), calculated using the method of Ackerberg et al. (2015).[46] In each case, I find significant positive effects, through the input channel, on quality, price or TFP. In addition, note that even if I did not make the CES assumption that allows me to derive a measure of quality and quality-adjusted prices, the other effects in Table 6.1 – on marginal costs (derived from a far weaker set of assumptions following De Loecker et al. (2016)) and on price, revenue and exit (all directly observed) – would all support a quality-upgrading interpretation, for instance in a model with linear demand as in Appendix 9.

Further robustness checks are provided in Appendices 10.B to 10.F. In turn, these control explicitly for potential confounding factors, use annual variation in tariffs, assess the impact of other recent reforms in India, check for selection effects caused by firms dropping out of the ASI census panel, and control for potential district-level trends. Finally, in Appendix 10.G I investigate whether the tendency of related industries to locate close to one another, rather than input-output relationships *per se*, could be driving the results. In all cases I confirm that the supply-driven quality-upgrading result is robust.

Comparing the channels: Turning to rows (ii)-(v) of Table 4.3, the model predicts that all five channels will affect the revenue and product exit margins. Table 6.3 shows the corresponding regression results. The revenue variable is in log form, so each coefficient represents the percentage impact of tariffs in the relevant channel being one percent higher in 2001. The exit variable is binary, so each coefficient is that of a linear probability model – i.e. each represents the marginal change in the probability of product exit resulting from the relevant tariffs being one percent higher in 2001.

The relationships are generally in the directions predicted by the model, with the input channel the only one that is significant on both variables, and indeed with relatively large magnitudes. As in the previous table, a 10% higher average tariff on inputs in 2001, and hence

[46]Such measures of productivity are subject to well-known biases (see, for instance, Foster et al. 2008, De Loecker & Goldberg 2014, Ackerberg et al. 2015, Orr 2019, Verhoogen 2020), but this evidence from a different measure is at a minimum indicative of an underlying change in fundamentals.

Table 6.2: Input effects of China's WTO accession – robustness checks

	Product-level				Firm-level	
	Quality	Price	Quality	Price	TFP	TFP
$InputTariff$ – DiD	0.278**	0.297**				
	(2.02)	(2.22)				
$InputFlow$ – ADH			0.684***	0.577**		
			(2.61)	(2.29)		
$InputTariff$ – DiD, firm-level					0.107***	
					(18.67)	
$InputFlow$ – ADH, firm-level						0.147***
						(28.78)
FEs	i,f,jt,st	i,f,jt,st	i,f,st	i,f,st	f,st	f,st
Controls	Yes	Yes	Yes	Yes	Yes	Yes
First Stage F-Stat			19.51	19.56		127.5
N	164,996	165,564	267,150	268,079	68,231	95,779

Notes: t-statistics in parentheses. * $p<0.10$, ** $p<0.05$, *** $p<0.01$. Standard errors clustered at the firm level. All variables in logs. DiD = difference-in-differences specification using 2001 tariff levels, as in Section 5.1. ADH = Autor, Dorn & Hanson (2013) specification using plausibly exogenous import and export flows, as in Section 5.2. All regressions include firm, product (for product-level regressions) and state-year FEs and control for rural/urban location, public/private ownership, and the other four channels (direct import competition, output effects, export competition and export opportunities). Models 1 and 2 also add sector-year FEs. Quality is calculated using the procedure of Khandelwal et al. (2013), and firm-level TFP is calculated using the procedure of Ackerberg et al. (2015).

a larger fall in tariffs post-accession, raises average product revenue in the post-accession period by 0.7% and lowers the probability of dropping the product by 0.18. While the model above only made qualitative predictions, rather than speaking to magnitudes, these results are consistent with the expectation from Figure 1.2 that China's expansion in the 2000s had particularly strong effects on India through the input channel.

Heterogeneity by firm size: Table 6.4 examines the heterogeneity of the quality-upgrading effect across the firm size distribution. I repeat the main regressions of Table 6.1 within four bins, each containing roughly a quarter of firms.[47] The quality-upgrading effect appears in all but the smallest firms. One possible explanation is that there is a fixed cost to reconfiguring supply to exploit new input opportunities, such that only larger and more productive firms are able to access new higher-quality inputs. An alternative but similar explanation relies on positive assortative matching, whereby larger and more productive firms have better access

[47]Non-census firms are now included, sacrificing the ability to examine the exit margin in favour of a representative sample of smaller firms.

Table 6.3: Impact of China's WTO accession on Indian firms, by channel

	Revenue	Exit
(i) *InputTariff*	0.0704**	-0.0180*
	(2.13)	(-1.95)
(ii) *CITariff*	0.198**	0.0106
	(2.29)	(0.49)
(iii) *OutputTariff*	-0.000777	-0.00526*
	(-0.07)	(-1.78)
(iv) *CRTariff*	-0.0435***	0.00650
	(-2.92)	(1.54)
(v) *ICTariff*	-0.0187	-0.00728
	(-0.42)	(-0.67)
FEs	i,f,st	i,f,st
Controls	Yes	Yes
N	175799	161072

Notes: t-statistics in parentheses. * p <0.10, ** p <0.05, *** p <0.01. Standard errors clustered at the firm level. All variables in logs, except *Exit* which is as described in Section 5.3. All regressions include firm, product and state-year FEs, and control for rural/urban location and public/private ownership. Each channel is measured as described in Section 5.1 – i.e. each coefficient gives the percentage (*Revenue*) or marginal (*Exit*) change in the average value of the outcome variable in the post-accession period resulting from a 1% higher pre-accession tariff on the relevant trade vector.

to the higher-quality input producers. In each case, quality upgrading in large firms could segment the market such that small firms compete on cost to sell lower-quality goods, or could reduce small firms' access to complementary inputs (e.g. skilled labour) which in turn reduces their quality and price. I leave full exploration of these possible mechanisms to future research.

Table 6.4: Heterogenous effects by number of employees

	0 – 20		20 – 100		100 – 350		350 +	
	Quality	Price	Quality	Price	Quality	Price	Quality	Price
Panel A: Full Sample								
$InputTariff$	-0.293*	-0.248*	0.404**	0.361**	0.257***	0.213***	0.214**	0.194**
	(-1.82)	(-1.65)	(2.25)	(2.23)	(2.88)	(2.81)	(2.16)	(2.16)
FEs	i,f,st	i,f,st	i,f,st	i,f,st	i,f,st	i,f,st	i,f,st	i,f,st
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	37117	37246	36966	37112	45528	45712	42248	42390
Panel B: Intensive Margin Only								
$InputTariff$	-0.0545	0.0265	0.303**	0.308**	0.292***	0.250***	0.231**	0.206**
	(-0.34)	(0.17)	(2.14)	(2.34)	(3.35)	(3.35)	(2.35)	(2.31)
FEs	i,f,st	i,f,st	i,f,st	i,f,st	i,f,st	i,f,st	i,f,st	i,f,st
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	13123	13157	18556	18610	37928	38060	36570	36698

Notes: t-statistics in parentheses. * p <0.10, ** p <0.05, *** p <0.01. Standard errors clustered at the firm level. All variables in logs. Panel A includes all products, while Panel B only includes those products which first appear in the dataset prior to China's WTO accession at the end of 2001. All regressions include firm, product and state-year FEs, and control for rural/urban location, public/private ownership, and the other four channels (direct import competition, output effects, export competition and export opportunities). Quality is calculated using the procedure of Khandelwal et al. (2013). The input channel is measured as described in Section 5.1 – i.e. each coefficient gives the percentage change in the average value of the outcome variable in the post-accession period resulting from a 1% higher average pre-accession tariff on the firm's inputs. The number of observations on quality is slightly lower within each bin because some firms which report price are missing other variables required to estimate quality.

7 Results: Spillovers

In this section I consider the broader spillovers of this core upgrading result. First, I unpack the dynamics to explore persistence over time. Second, I trace the propagation of the quality effect along supply chains, to explore the role of production networks in amplifying the initial effect.

7.1 Persistence over time

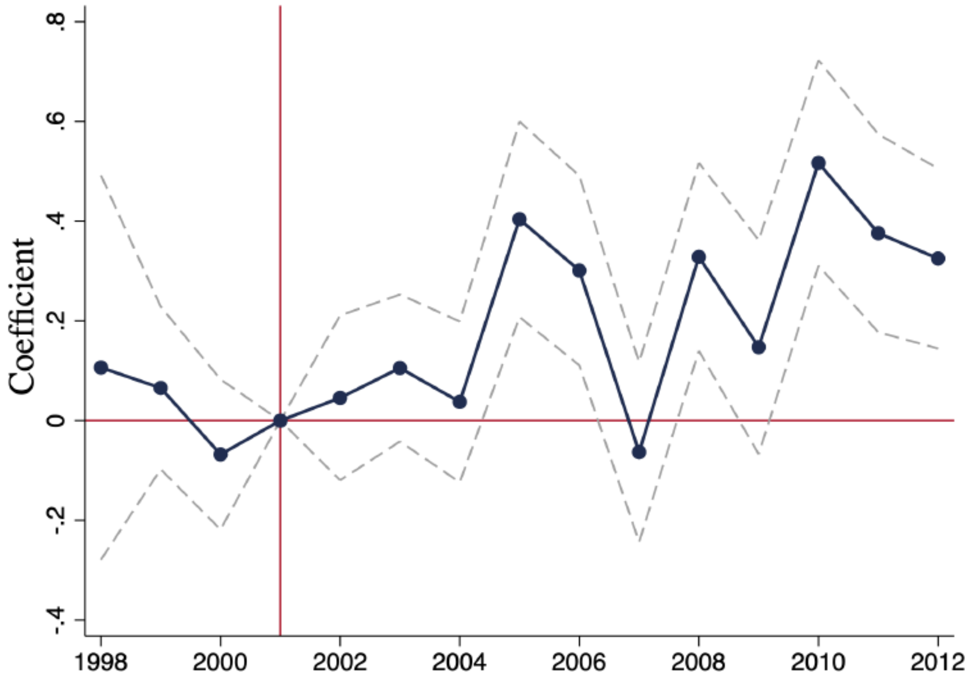
While Table 6.1 shows the average effect of tariff changes before vs. after 2001, it provides no insight into the dynamics of the rise in quality. I therefore interact 2001 tariff levels in each channel with dummies for each year, to ascertain the marginal impact in each year of having higher tariffs in 2001. The interaction coefficients for the input channel are shown in Figure 7.1. Note that the underlying trend in price and quality has been removed by the time fixed effects, so each of the graphs shows the *additional* percentage rise in price and quality for a product with a 1% higher tariff on inputs in 2001.

There is no significant effect in 1998-2000 relative to the 2001 baseline, for either price or quality, so there is no reason to reject the parallel pre-trends assumption. If anything, the marginal effect of having high 2001 tariffs was falling in those years, making its subsequent reversal more striking. Price and quality are then higher in high-2001-tariff products in all but one year in the decade following China's WTO accession, and significantly so in at least six years.[48] At the peak in 2010, products with a 10% higher input tariff in 2001 have 5.2% higher prices and 5.3% higher quality. The quality-upgrading effect is remarkably persistent, with prices and quality still significantly higher for affected products more than ten years after China's WTO accession. Moreover, the results so far only reflect the direct one-step impact of inputs on quality – they do not take into account the role of the wider production network. This is examined in the next section.

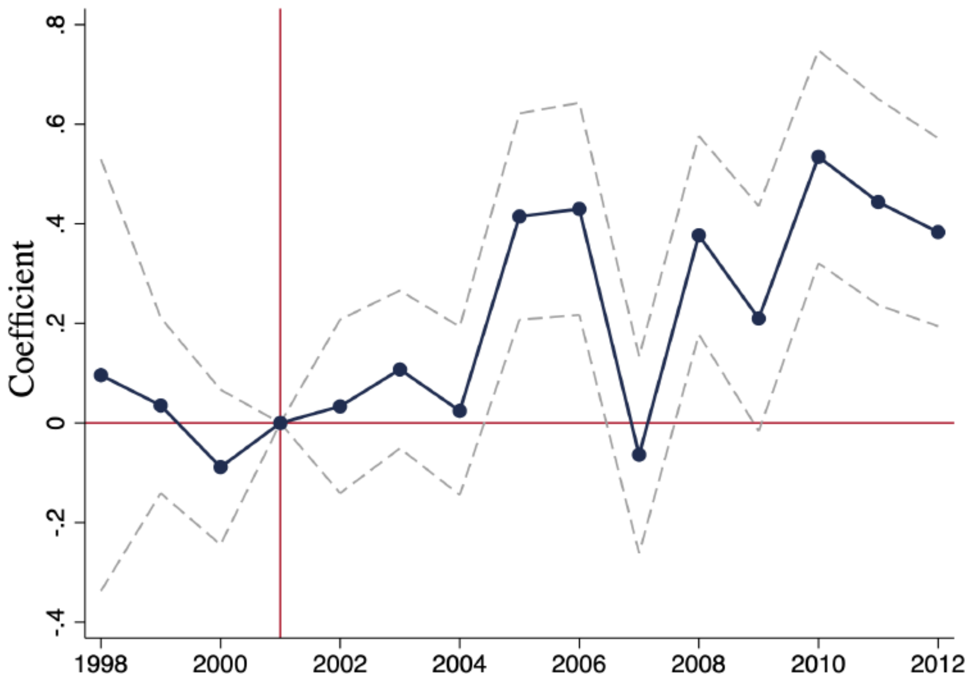
[48] Recall that the label '2007' in Figure 7.1 refers to the Indian financial year 2007-08 – the relative quality upgrade of the 'treated' firms paused during the Financial Crisis, before swiftly rebounding.

Figure 7.1: The dynamics of quality upgrading

(a) Price



(b) Quality

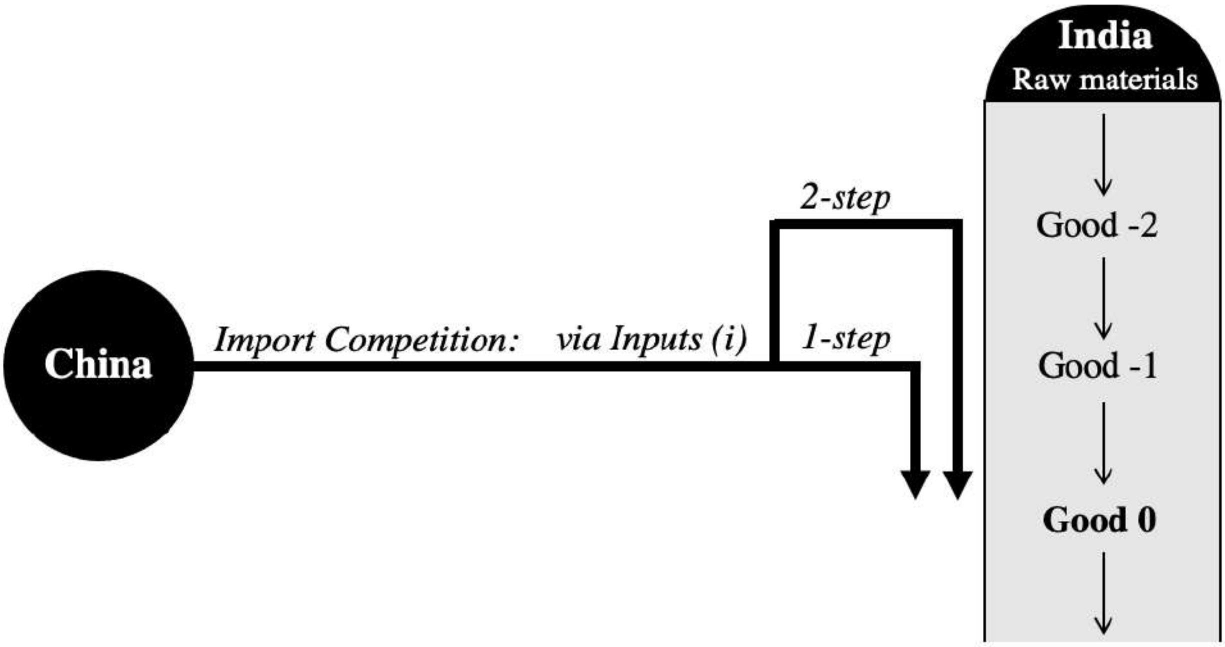


Notes: These graphs plot the coefficients on the interactions of 2001 input tariff levels with each year, relative to the 2001 baseline. The dashed lines show the 95% confidence interval. The underlying regression also interacts the year with each of the other channels, to control for the dynamics in each of direct import competition, output effects, export competition and export opportunities. The regression also includes firm, product and state-year fixed effects and clusters at the firm level, as in Table 6.1.

7.2 Propagation across the production network

The input channel and output channel measures described thus far are only informative on the direct spillovers from import competition, i.e. the 'one-step' impact on firms immediately ahead or behind in the supply chain. This matches the stylised supply chain in Figure 1.3, but may miss important aspects of reality. Consider instead Figure 7.2, which zooms in on the input channel and depicts a slightly longer supply chain. In addition to the previous channel, improved access to inputs can now also affect Good 0 through Good -2, via knock-on effects on Good -1. In other words, if Good 0's input suppliers in turn have better access to inputs, any quality upgrade to Good -1 could cascade onto Good 0.[49]

Figure 7.2: Input effects along the supply chain



Notes: This figure zooms in on the input channel in Figure 1.3, and presents a slightly longer supply chain to allow for 'two-step' effects. Thin lines depict the Indian manufacturing supply chain, and thick lines represent the effects of China's exports.

To test for such effects, I construct intermediate measures of the 'two-step', 'three-step' (and so on) impacts on firms along the supply chain by repeatedly summing over the input value shares. For each measure of import competition M_{it} (i.e. $CITariff_{i,2001}$, $CIFlow_{it}$ or

[49] Analogous effects could occur for the output channel. Denote the firm using a product as an input the 'customer', as in Section 4, for simplicity. Then if Good 0's customer's customer faces increased import competition from China, this could concertina back up the supply chain to reduce demand for Good 0.

$CIFlow_{it}^{IV}$), I therefore have:

$$\begin{array}{lll} \text{One-step spillovers:} & InputM1_{it} = & \sum_k \alpha_{ik} \cdot M_{kt} \\ \text{Two-step spillovers:} & InputM2_{it} = & \sum_l \alpha_{il} \sum_k \alpha_{lk} \cdot M_{kt} \\ \text{Three-step spillovers:} & InputM3_{it} = & \sum_m \alpha_{im} \sum_l \alpha_{ml} \sum_k \alpha_{lk} \cdot M_{kt} \\ \vdots & \vdots & \vdots \end{array} \tag{7.1}$$

These in turn reflect the effect on product i of increased import competition in the markets for its inputs, its inputs' inputs, its inputs' inputs' inputs, and so on. I also construct equivalent measures for the output channel, by repeatedly summing over the usage shares γ_{ik}.

With these measures in hand, I repeat the baseline specification but include a further four 'degrees' of input spillovers, plus four further 'degrees' of output spillovers to ensure the controls are symmetric.[50] Figure 7.3 illustrates the results for price and quality. Increased import competition in the markets for Good -2 and Good -1 has significant positive effects on the price and quality of Good 0. In other words, improved access to the first good in the supply chain doesn't just drive quality upgrading in the product using it as a component – it also has a knock-on upgrading effect on the *next* good in the supply chain. (Effects beyond two steps are not significant, and not shown as the large standard errors would require a substantial rescaling of the y-axis, obscuring the other effects.)

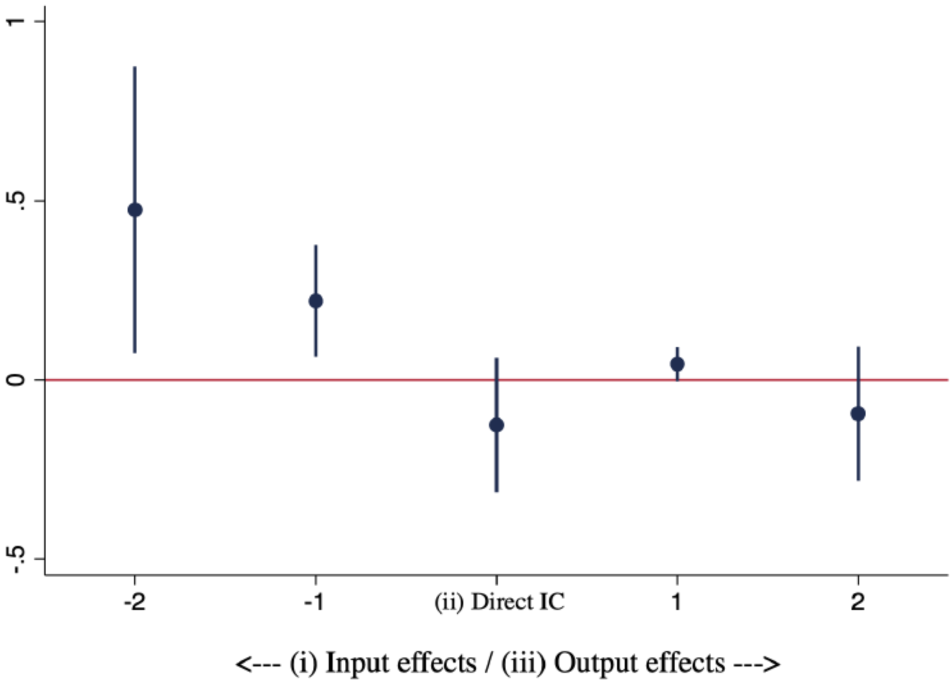
Having established that upgrading effects propagate along the supply chain, the next step is to understand the full impact of these ripple effects. As is clear from the input-output network in Figure 3.2, the linear supply chain effects examined so far remain highly simplistic. Consider finally Figure 7.4, in which various input goods interact. Good 0 is now subject to one-step effects from Good -1, two-step effects from Goods -2A and -2B, and potentially even further effects if, for instance, the dashed supply relationships also exist.

To take such broader production linkages into account, I therefore follow Lane (2019) in using the Leontief inverse to take into account all input and output effects up to the 'nth-degree'. First define $\mathbf{A}$ as the matrix of the value share coefficients α_{ik} described in Section 5.1, and note that total output of each good (collected in vector $\mathbf{x}$) is equal to output for use as an intermediate input $\mathbf{Ax}$ plus output for final consumption $\mathbf{d}$: $\mathbf{x} \equiv \mathbf{Ax} + \mathbf{d}$.

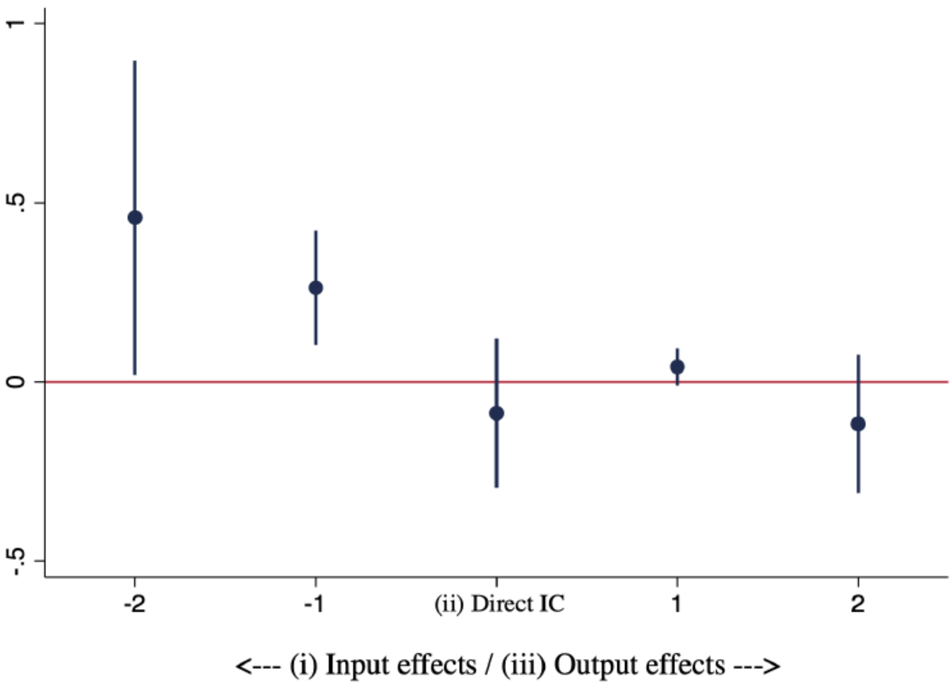
[50] Beyond this number of degrees, multicollinearity problems become severe and I lack sufficient observations or sufficient granularity in the input-output table to distinguish separate effects by degree.

Figure 7.3: Upgrading effects along the supply chain

(a) Price

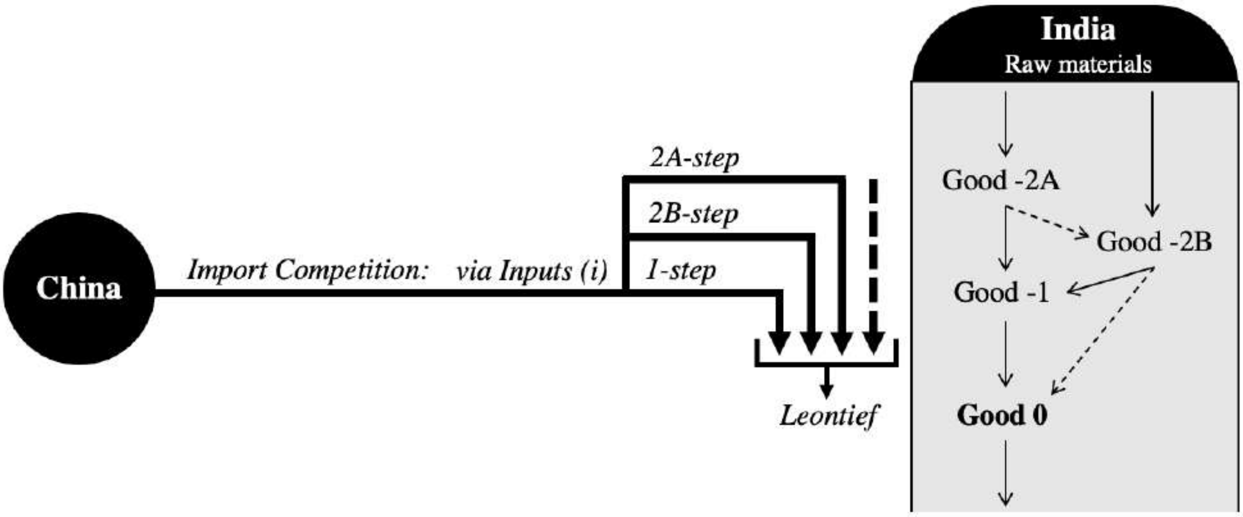


(b) Quality



Notes: These graphs show the effects on Good 0 of import competition at different points in the supply chain. For instance, the point '-1' shows the effect on the price or quality of Good 0 of an increase in import competition in the market for its immediate inputs. Each coefficient is from a regression as in equation 5.3, except including five degrees of input effects and five degrees of output effects. Error bars are shown at the 5% significance level, and coefficients on input/output effects are insignificant outside of the range shown.

Figure 7.4: Input effects along the supply chain



Notes: This figure zooms in further on the input channel in Figures 1.3 and 7.2, showing the upstream portion of a stylised production network centred on Good 0. Thin lines depict the Indian manufacturing supply chain, and thick lines represent the effects of China's exports. The dashed lines are examples of potential additional relationships that would also be captured by the Leontief measure.

Rearranging gives $\mathbf{x} \equiv (\mathbf{I} - \mathbf{A})^{-1}\mathbf{d}$, and hence the Leontief inverse $\mathbf{L}$ in equation 7.3:

$$\boldsymbol{A} \equiv \begin{bmatrix} \alpha_{11} & \alpha_{12} & \dots & \alpha_{1k} \\ \alpha_{21} & \alpha_{22} & \dots & \alpha_{2k} \\ \vdots & \vdots & \ddots & \vdots \\ \alpha_{i1} & \alpha_{i2} & \dots & \alpha_{ik} \end{bmatrix} \tag{7.2}$$

$$\mathbf{L} \equiv (\mathbf{I} - \mathbf{A})^{-1} \equiv \begin{bmatrix} l_{11} & l_{12} & \dots & l_{1k} \\ l_{21} & l_{22} & \dots & l_{2k} \\ \vdots & \vdots & \ddots & \vdots \\ l_{i1} & l_{i2} & \dots & l_{ik} \end{bmatrix} \tag{7.3}$$

Each coefficient l_{ik} reflects the increase in production of i necessary to meet a one unit increase in final demand of k, taking into account all the interlinkages in the economy. This includes not just production of i as a direct input to k, but also as an input to other inputs to k, and so on. Substituting l_{ik} for γ_{ik} in equations 5.2, 5.6 and 5.11 therefore takes into account the total cumulated exposure to import competition of the sectors that i supplies (and of the sectors those sectors supply, and so on).[51] Similarly, substituting l_{ki} for α_{ik} in equations 5.1, 5.5 and 5.10 takes into account the total cumulated exposure to import competition of sector i's inputs (and the inputs to those inputs, and so on). This gives the new input channel variables:

$$\text{Total cumulated spillovers:}^{52} \qquad InputMT_{it} = \sum_{k} l_{ki} \cdot M_{kt} \tag{7.4}$$

where again M_{it} represents each of the import competition measures, and I also construct the equivalent variables for the output channel by substituting l_{ik} for l_{ki}.

Table 7.1 repeats the baseline regressions using the Leontief measures. All significant coefficients are now larger, implying that interlinkages within the production network amplify the effect of China's WTO accession. Figure 7.5 compares the dynamics of price and quality when using both the one-step and full network measures. The amplification effect of the production network is clear. At the peak in 2010, products with a 10% higher input tariff in 2001 now have 8.7% higher prices and 9.4% higher quality – i.e. the effect is up to 75% larger, relative to the one-step measure.

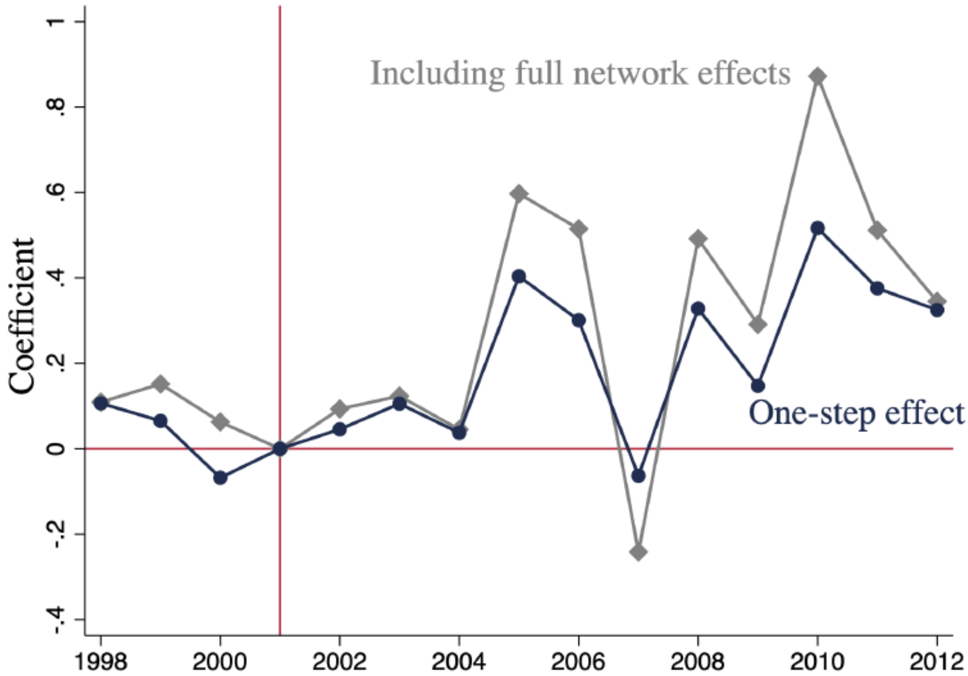
I therefore conclude that the production network plays an important role in propagating quality shocks downstream. How does the post-2001 Chinese input shock compare to an 'ideal' positive supply shock, from a policy perspective? As Acemoglu et al. (2012) observe, supply shocks in sectors with strong downstream connections (i.e. in sectors which supply many other sectors, whether directly or through or higher-degree linkages) have larger aggregate impacts. Returning to Figure 3.2, I note that the sectors with the largest increases in Chinese imports are generally neither multi-purpose raw materials (in the very centre of the network, with many downstream connections), nor final goods (towards the edge, with fewer) – instead they are mostly sophisticated manufactured inputs, in an intermediate ring. From a development perspective, the 'ideal' quality-upgrading supply shock would occur in the most central nodes of Figure 3.2, so that the amplification effect through downstream, forward linkages is the largest. However, in practice such raw materials and commodities may have the least scope for quality improvements. Thus, in broad terms, the 'China shock' was well-placed to have significant upgrading benefits for India, and for developing countries with a similar

[51] As in Section 5.1 above, set diagonals l_{ii} to zero to avoid double-counting the direct import competition channel.

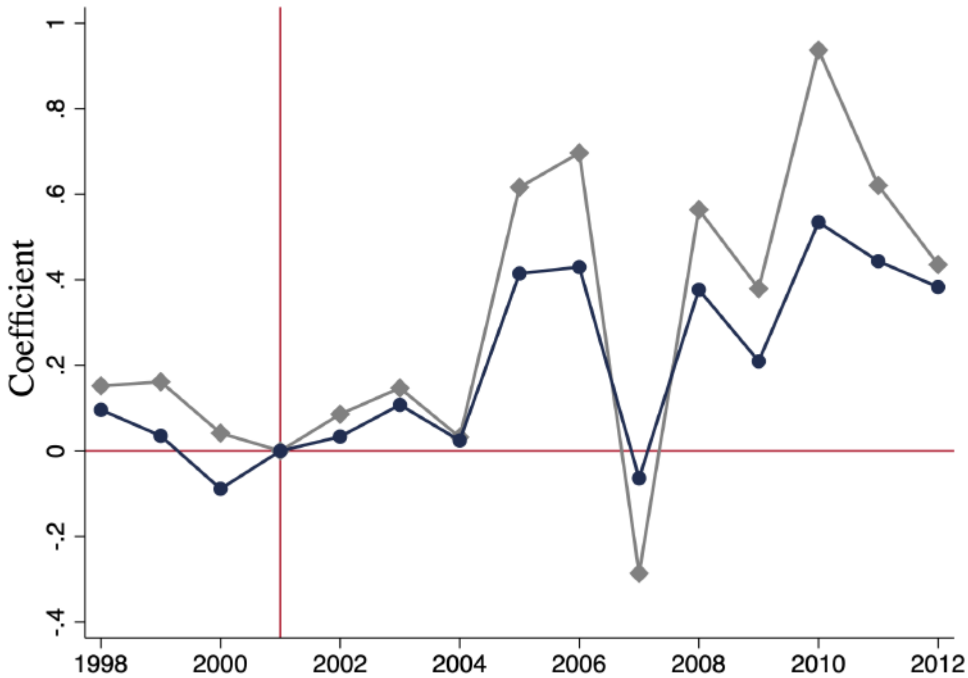
[52] Crucially, the Leontief version reflects the cumulation of all degrees of spillovers, rather than merely the 'nth-degree' effect alone – which fades to zero for sufficiently large n, since nearly all γ_{ik} and α_{ik} are less than one.

Figure 7.5: Upgrading dynamics, including effect of production network

(a) Price



(b) Quality



Notes: These graphs again plot the coefficients on the interactions of 2001 input tariff levels with each year, relative to the 2001 baseline. The dark blue points remain the coefficients estimated using the one-step measures, as in Figure 7.1. The grey line instead uses the Leontief-coefficient-based measures described in Section 7.2, which take into account all interlinkages within the production network. Again, each underlying regression also interacts the year with each of the other channels, to control for the dynamics of direct import competition, output effects, export competition and export opportunities. Each regression also includes firm, product and state-year fixed effects and clusters at the firm level, as in Tables 6.1 and 7.1.

Table 7.1: Impact of China's WTO accession – across full production network

	MCs	Quality	Price	QAP	Quantity	Revenue	Exit
Panel A: Full Sample							
$InputTariffT$	0.374***	0.247***	0.199***	-0.0450**	-0.0807	0.111***	-0.0292**
	(2.78)	(3.92)	(3.36)	(-2.54)	(-1.09)	(2.59)	(-2.48)
FEs	i,f,st	i,f,st	i,f,st	i,f,st	i,f,st	i,f,st	i,f,st
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	34408	165011	165579	165011	165017	175799	161072
Panel B: Intensive Margin Only							
$InputTariffT$	0.368***	0.254***	0.206***	-0.0416**	-0.100	0.104**	-0.0263**
	(2.71)	(4.03)	(3.49)	(-2.33)	(-1.36)	(2.43)	(-2.22)
FEs	i,f,st	i,f,st	i,f,st	i,f,st	i,f,st	i,f,st	i,f,st
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	28460	137780	138229	137780	137785	147843	139739

Notes: t-statistics in parentheses. * p <0.10, ** p <0.05, *** p <0.01. Standard errors clustered at the firm level. All variables in logs, except *Exit* which is as described in Section 5.3. Panel A includes all products, while Panel B only includes those products which first appear in the dataset prior to China's WTO accession at the end of 2001. All regressions include firm, product and state-year FEs, and control for rural/urban location, public/private ownership, and the other four channels (direct import competition, output effects, export competition and export opportunities). Quality and quality-adjusted prices are calculated using the procedure of Khandelwal et al. (2013), and marginal costs are calculated using the procedure of De Loecker et al. (2016). The input channel is measured as described in section 7.2: each coefficient gives the percentage change in the average value of the outcome variable in the post-accession period resulting from a 1% higher average pre-accession tariff on the Leontief-coefficient-weighted average of all the direct and indirect inputs to a firm across the whole production network.

manufacturing structure.[53]

[53] Conversely, the 'ideal' positive demand shock would occur in the most sophisticated final goods, i.e. those with lots of upstream linkages, as this would then benefit the long chains of producers back up the supply chain. For developing countries, this has generally not been the case with the China shock – instead Chinese demand has mostly been for primary commodities (as in e.g. Costa et al. 2016).

8 Conclusion

During the 2000s, China rapidly became a major provider of intermediate inputs to many developing countries. This paper exploits China's accession to the WTO to investigate the impact on Indian manufacturing firms. Consistent with a model of multi-product manufacturers gaining access to higher-quality components, a larger fall in the tariffs faced by Chinese inputs raises revenue, quality and prices whilst lowering quality-adjusted prices and the probability of product exit. These effects are driven by the upgrading of existing products, unlike in the widely studied Indian trade liberalisation of the early 1990s.

This supply-driven quality-upgrading effect persists for at least ten years, peaking in 2010. It also cascades along the supply chain: a shock to one input drives quality upgrading not only in the product which uses it, but also in the next product down the supply chain. Broader linkages in the production network further spread the upgrading effect, amplifying the one-step impact by up to 75%. In contrast to existing literature focused on negative demand effects of the 'China shock' in developed countries, these results highlight the potential for positive supply effects in many developing countries.

As with Lane (2019) and Liu (2019) for industrial policy, this study affirms the importance of understanding the production network context when setting international trade policy. The supply-driven quality-upgrading channel represents an additional source of 'gains from trade' forgone by India in rejecting the Regional Comprehensive Economic Partnership with large Asian economies. From a development perspective, the 'ideal' trade deal (i) improves import access to inputs as far upstream as possible, so that there is the maximum potential for benefits to spill downstream, and (ii) improves export access to the ultimate (i.e. 'most downstream') consumers, so that there is the longest possible chain of upstream firms to benefit from supplying them. Future policy work could explore the most promising trade deals from this perspective.

Finally, two main areas for future research stand out: (i) understanding the aggregate welfare implications of the supply-driven quality-upgrading mechanism, and whether a similar effect occurred in other countries with a similar initial level of manufacturing development to India, and (ii) understanding the role of the production network in amplifying negative input supply shocks, such as those caused by the Covid-19 pandemic.

9 Theoretical Appendix

This Appendix derives similar predictions to those in Section 4 under the alternative assumption of linear demand. First, replace equation 4.1 with:

$$U = x_0 + \beta \int_{i\in\Omega} q_i x_i di - \frac{1}{2}\gamma \int_{i\in\Omega} (q_i x_i)^2 di - \frac{1}{2}\eta \Big[\int_{i\in\Omega} q_i x_i di \Big]^2 \tag{9.1}$$

giving demand $x_i = \frac{R}{\gamma q_i}(\hat{P} - \frac{p_i}{q_i})$, where $P = \frac{1}{M}\int_{i\in\Omega}\frac{p_i}{q_i}di$ and $\hat{P} = \frac{\eta \int_{i\in\Omega}\frac{p_i}{q_i}di + \beta\gamma}{\eta M + \gamma}$ is the quality-adjusted 'choke price' above which demand is zero, with M the total number of (horizontally-differentiated) varieties available.[54] Profit maximisation by firms then gives:

$$\begin{array}{llcll}
\text{Price} & p_i(\phi_f, \lambda_{fi}) & = & \frac{1}{2} & \Big[\hat{P}(\phi_f\lambda_{fi}q_m)^{\theta+1} + m\phi_f\lambda_{fi}\Big] \quad (9.2) \\
\text{Quantity} & x_i(\phi_f, \lambda_{fi}) & = & \frac{R}{2\gamma} & \Big[\hat{P}(\phi_f\lambda_{fi}q_m)^{-(\theta+1)} - m(\phi_f\lambda_{fi})^{-2\theta-1}q_m^{-2(\theta+1)}\Big] \\
\text{Revenue} & r_i(\phi_f, \lambda_{fi}) & = & \frac{R}{4\gamma} & \Big[\hat{P}^2 - m^2(\phi_f\lambda_{fi})^{-2\theta}q_m^{-2(\theta+1)}\Big] \quad (9.4) \\
\text{Mark-up} & \mu_i(\phi_f, \lambda_{fi}) & = & \frac{1}{2} & \Big[\hat{P}(\phi_f\lambda_{fi})^{\theta}q_m^{\theta+1}m^{-1} + 1\Big] \quad (9.5) \\
\text{Profit} & \pi_i(\phi_f, \lambda_{fi}) & = & \frac{R}{4\gamma} & \Big[\hat{P} - m(\phi_f\lambda_{fi})^{-\theta}q_m^{-(\theta+1)}\Big]^2 \quad (9.6)
\end{array}$$

Model improved access to new components as rises in q_m and m where $\frac{(\Delta q_m)^{\theta+1}}{\Delta m} > 1$ – i.e. let the rise in input quality outweigh the rise in input price, as in equation 4.9. Then model increased import and export competition as rises in M, output effects as a fall in R, and increased export opportunities as a rise in R. The resulting effects on observables are shown in Table 9.1. All predictions are qualitatively the same as in Table 4.3, except that prices now fall under direct import and export competition (as prices are no longer a constant mark-up over costs, as in the CES case).[55] The results in Section 6 are thus robust to using linear rather than CES demand.

[54] Note that, with linear demand, headquarter and product-line fixed costs are no longer required for demand to fall to zero in a sufficiently expensive product.

[55] I do not consider the impacts on quality-adjusted prices under linear demand, as these are only 'observed' when assuming CES as per Khandelwal et al. (2013). I leave quality q_i in Table 9.1 for reference, but I also do not observe this when assuming linear demand. Quality effects are instead inferred from the impacts on marginal cost, price and revenue, in the spirit of Verhoogen (2008) and Kugler & Verhoogen (2012).

Table 9.1: The China shock and observables – linear demand

		Channel	Shock	c_i	q_i	p_i	x_i	r_i	Ex_i
Import Competition:	(i)	via Inputs	$\uparrow q_m > \uparrow m$	$\uparrow$	$\uparrow$	$\uparrow$	$\sim$	$\uparrow$	$\downarrow$
	(ii)	Direct	$\uparrow M \rightarrow \downarrow \hat{P}$	–	–	$\downarrow$	$\downarrow$	$\downarrow$	$\uparrow$
	(iii)	via Outputs	$\downarrow R$	–	–	–	$\downarrow$	$\downarrow$	$\uparrow$
Exports:	(iv)	Competition	$\uparrow M \rightarrow \downarrow \hat{P}$	–	–	$\downarrow$	$\downarrow$	$\downarrow$	$\uparrow$
	(v)	Opportunity	$\uparrow R$	–	–	–	$\uparrow$	$\uparrow$	$\downarrow$

Notes: This table summarises, for each channel, the predicted effects on variables which can be observed in or derived from the ASI data. From left to right, the outcome variables are: c_i – marginal cost; q_i – quality; p_i – price; x_i – quantity; r_i – revenue; Ex_i – probability of dropping the product next period.

10 Empirical Appendix

10.A Estimating the elasticity of substitution

This paper currently uses $\sigma = 3.7$, the median elasticity of substitution across Indian goods calculated by Broda et al. (2006). Future work would ideally use industry-specific estimates, as in Bajgar & Javorcik (2016). Without such estimates available, using $\sigma = 3.7$ is a reasonable approximation: it is close to the typical median value for σ, 3.4, across all countries in Broda et al.'s study, and the authors also find that median elasticities do not differ significantly across product types – i.e. between commodities vs. reference-priced goods vs. differentiated goods (Broda et al. 2006).

10.B Further controls

In an additional precaution against misattribution, I test for robustness to various possible confounding factors. Higher initial tariffs may reflect the lobbying power of large or well-connected industries, which may itself generate faster rises in quality or price over time.[56]

[56] For example, lobbying has influenced Indian trade policy on spirits (which became the subject of an official complaint to the WTO by the EU (Sen 2007, World Trade Organisation 2008)), wine (see, for instance, telegraph.co.uk/finance/.../Tax-deal-to-uncork-India-for-wine-investors) and motorcycles (see economictimes.indiatimes.com/news/.../50-tariff-on-us-motorcycles-by-india-unacceptable-says-donald-trump). Thus while there is some evidence of strategic manipulation, it tends to be substantial in only narrow sectors with well-organised lobbies. Moreover, it is not clear that such tariffs allow for improved performance over time – they may instead encourage stagnation by reducing competition. Nonetheless, I control for correlates of such lobbying as a precaution.

Similarly, infant industry arguments or political concerns may encourage the government to protect labour-intensive industries or those paying high wages. Following Lu & Yu (2015), I account for these specific political and economic factors by controlling for five industry-level variables: log total employment, log total sales, the share of public firms, the capital-labour ratio and log average wage per worker. Table 10.1 shows the results: the main results for quality and price (repeated in columns 1 & 5 for convenience) are barely affected, whether including additional controls with annual variation (columns 2 & 6), or with their 2001 level interacted with the post-2001 dummy (3 & 7), or both (4 & 8).

Table 10.1: Input effects of China's WTO accession – additional controls

	Log Quality				Log Price			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
InputTariff	0.238***	0.217***	0.268***	0.256***	0.194***	0.179***	0.228***	0.221***
	(4.27)	(4.15)	(4.54)	(4.36)	(3.72)	(3.66)	(4.16)	(4.02)
Log Employment$_t$		-0.136***		-0.147***		-0.0568***		-0.0719***
		(-10.00)		(-8.81)		(-4.54)		(-4.73)
Log Sales$_t$		0.194***		0.198***		0.0682***		0.0773***
		(16.82)		(14.01)		(6.45)		(5.99)
Share of Public Firms$_t$		0.109		0.187*		0.0540		0.143
		(1.26)		(1.73)		(0.66)		(1.43)
K-L Ratio$_t$		0.000292		0.000210		0.000582**		0.000438
		(0.91)		(0.64)		(1.96)		(1.43)
Log Average Wage$_t$		-0.0169		-0.0481		0.0293		-0.00258
		(-0.55)		(-1.31)		(1.05)		(-0.08)
Post2001$_t$ × Log Employment$_{2001}$			0.0633*	0.00671			0.0177	-0.00833
			(1.93)	(0.20)			(0.57)	(-0.26)
Post2001$_t$ × Log Sales$_{2001}$			-0.0777***	-0.0223			-0.0351	-0.0117
			(-3.17)	(-0.90)			(-1.53)	(-0.50)
Post2001$_t$ × Share of Public Firms$_{2001}$			0.613**	0.733***			0.658***	0.727***
			(2.36)	(2.76)			(2.65)	(2.85)
Post2001$_t$ × K-L Ratio$_{2001}$			0.00602**	0.00493*			0.00427	0.00387
			(2.17)	(1.77)			(1.64)	(1.47)
Post2001$_t$ × Log Average Wage$_{2001}$			-0.0645	-0.0917			-0.0961*	-0.111**
			(-1.15)	(-1.59)			(-1.82)	(-2.06)
FEs	i,f,st	i,f,st	i,f,st	i,f,st	i,f,st	i,f,st	i,f,st	i,f,st
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	165011	162961	131041	130049	165579	163523	131472	130477

Notes: t-statistics in parentheses. * p <0.10, ** p <0.05, *** p <0.01. Standard errors clustered at the firm level. All regressions include firm, product and state-year FEs and control for rural/urban location, public/private ownership, and the other four channels (direct import competition, output effects, export competition and export opportunities). Quality is calculated using the procedure of Khandelwal et al. (2013). The input channel is measured as described in Section 5.1 – i.e. each coefficient in the first row gives the percentage change in the average value of the outcome variable in the post-accession period resulting from a 1% higher average pre-accession tariff on the firm's inputs.

10.C Annual tariffs

I also check the robustness of results to using an annual tariff specification, rather than the difference-in-differences method outlined in Section 5.1. While this is more vulnerable to endogeneity concerns, as noted in the main text, it does allow more of the variation in the tariff variable to be used. I follow Brandt et al. (2017) in regressing each dependent variable on tariffs in each year:

$$\begin{aligned} \ln y_{ift} = {} & \alpha_{(i)} \cdot \ln InputTariff_{it} \\ & + \alpha_{(ii)} \cdot \ln CITariff_{it} \\ & + \alpha_{(iii)} \cdot \ln OutputTariff_{it} \\ & + \alpha_{(iv)} \cdot \ln CRTariff_{it} \\ & + \alpha_{(v)} \cdot \ln ICTariff_{it} \\ & + \boldsymbol{\alpha}'\mathbf{X}_{ft} + a_i + b_f + c_{st} + u_{ift} \end{aligned} \tag{10.1}$$

where I first multiply each outcome variable y_{ift} by minus one, such that each coefficient α reflects the average percentage change in y_{ift} associated with a one percent *fall* in the respective tariff. The results are shown in Table 10.2. All relationships are in the same direction as with the difference-in-differences specification, and all previously significant relationships remain so, except for the exit margin. Once again, lower tariffs on inputs allow output quality to rise, and by more than prices, so that quality-adjusted output prices fall and revenue rises.

Table 10.2: Input effects of China's WTO accession – annual tariffs

	MCs	Quality	Price	QAP	Quantity	Revenue	Exit
Panel A: Full Sample							
$InputTariff_t$	0.267***	0.292***	0.218***	-0.0730***	-0.0218	0.152***	-0.00209
	(4.09)	(9.02)	(7.74)	(-7.03)	(-0.63)	(6.46)	(-0.32)
FEs	i,f,st	i,f,st	i,f,st	i,f,st	i,f,st	i,f,st	i,f,st
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	30131	149471	150084	149471	149479	160583	160649
Panel B: Intensive Margin Only							
$InputTariff_t$	0.273***	0.302***	0.221***	-0.0791***	-0.00942	0.169***	-0.00234
	(4.00)	(8.78)	(7.40)	(-7.44)	(-0.27)	(7.14)	(-0.34)
FEs	i,f,st	i,f,st	i,f,st	i,f,st	i,f,st	i,f,st	i,f,st
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	27618	136506	137031	136506	136513	147049	147114

Notes: t-statistics in parentheses. * p <0.10, ** p <0.05, *** p <0.01. Standard errors clustered at the firm level. All variables in logs, except *Exit* which is as described in Section 5.3. All regressions include firm, product and state-year FEs, and control for rural/urban location, public/private ownership, and the other four channels (direct import competition, output effects, export competition and export opportunities). Quality and quality-adjusted prices are calculated using the procedure of Khandelwal et al. (2013), and marginal costs are calculated using the procedure of De Loecker et al. (2016). The input channel is measured as described in Appendix 10.C – i.e. each coefficient reflects the average percentage change in the outcome variable associated with a one percent fall in the average tariff on the firm's inputs.

10.D Impact of other reforms in India

Several major reforms occurred in India during the 1990s and 2000s, but many had reached their conclusion by the beginning of the period considered here.[57] Almost 85% of industries had been delicensed by 1991, more than 90% by 2000, and almost all of these delicensed industries were eligible for automatic FDI approval by 2001 (Harrison et al. 2013, Arnold et al. 2016). The Indian government substantially reduced tariffs on many industrial goods in 2005 (World Bank 2006, Virmani 2005), but this reform was a continuation of the earlier trend in tariff reduction – as shown in Figure 5.1 Panel (a). Panel (b) shows a delayed impact of this reform on imports from China, which do not spike until 2006.

To alleviate possible concerns about endogeneity of these tariff changes, I therefore run additional robustness checks on the limited sample from 1998-2005, as shown in Table 10.3. The quality-upgrading effect still holds, in both product- and firm-level regressions and using both the difference-in-differences and Autor et al. (2013) methods, with the results merely

[57] An exception is service sector liberalisation, discussed in Arnold et al. (2016), which may have magnified the impact of China's WTO accession. An exploration of the interaction effects between goods tariff declines and service sector liberalisation is left for future work.

slightly less significant due to the smaller sample.[58]

Table 10.3: Input effects of China's WTO accession – 1998-2005 only

	Product-level				Firm-level	
	Quality	Price	Quality	Price	TFP	TFP
$InputTariff$ – DiD	0.176***	0.164***				
	(3.52)	(3.64)				
$InputFlow$ – ADH			3.370*	3.030*		
			(1.94)	(1.94)		
$InputTariff$ – DiD, firm-level					0.0618***	
					(8.30)	
$InputFlow$ – ADH, firm-level						0.150***
						(14.78)
FEs	i,f,st	i,f,st	i,f,st	i,f,st	f,st	f,st
Controls	Yes	Yes	Yes	Yes	Yes	Yes
First Stage F-Stat			1.24	1.191		121.7
N	53,025	53,053	70,201	70,240	24,597	27,434

Notes: t-statistics in parentheses. * p <0.10, ** p <0.05, *** p <0.01. Standard errors clustered at the firm level. All variables in logs. DiD = difference-in-differences specification using 2001 tariff levels, as in Section 5.1. ADH = Autor, Dorn & Hanson (2013) specification using plausibly exogenous import and export flows, as in Section 5.2. All regressions include firm, product (for product-level regressions) and state-year FEs and control for rural/urban location, public/private ownership, and the other four channels (direct import competition, output effects, export competition and export opportunities). Quality is calculated using the procedure of Khandelwal et al. (2013), and firm-level TFP is calculated using the procedure of Ackerberg et al. (2015).

10.E Census selection and the exit variable

Since the ASI is only a census for firms with more than 100 workers, a given firm-product exit from the data could be either a genuine exit or the result of the firm falling below the size threshold for the census panel. To test whether the latter is driving the results, I repeat the exit regressions using only the subset of firm-product exits for which the same firm continues in the panel – i.e. using only those product exits which are known to be due to the firm dropping the product, not the firm itself exiting. The results are shown in Table 10.4, for both the original exit variable and the new refined version. The results remain very similar, suggesting that census selection is not driving the exit effects. Indeed, the number of firm-product exits is only slightly lower in the refined version, implying a relatively limited

[58] The over-large coefficients reported for the ADH method, in the third and fourth columns, reflect that the instruments are now much weaker than in Table 6.2. This is because China's export expansion did not take off in many countries until 2003, or even later (see Figure 1.1 for example), so there is limited variation in the instruments.

role for firm (rather than firm-product) exit among these large firms.

Table 10.4: Robustness of the exit variable to sample selection

	Exit	
	Original	Refined
(i) $InputTariff$	-0.0180*	-0.0180*
	(-1.95)	(-1.93)
(ii) $CITariff$	0.0106	-0.0374*
	(0.49)	(-1.68)
(iii) $OutputTariff$	-0.00526*	-0.00910***
	(-1.78)	(-3.10)
(iv) $CRTariff$	0.00650	0.00131
	(1.54)	(0.31)
(v) $ICTariff$	-0.00728	-0.00656
	(-0.67)	(-0.60)
FEs	i,f,st	i,f,st
Controls	Yes	Yes
Number of firm-product exits	93464	70062
Observations	161072	161072

Notes: t-statistics in parentheses. * p <0.10, ** p <0.05, *** p <0.01. Standard errors clustered at the firm level. *Exit* measured as described in Section 5.3. The second column refines the exit variable to include only those firm-product exits for which the firm is not also exiting – i.e. only those exits which could not be caused by the firm falling below the census cutoff. All regressions include firm, product and state-year FEs, and control for rural/urban location and public/private ownership. Each channel is measured as described in Section 5.1 – i.e. each coefficient gives the marginal change in the probability of exit in the post-accession period resulting from a 1% higher pre-accession tariff on the relevant trade vector.

10.F District-time fixed effects

Table 10.5 repeats the baseline regressions using district-time, rather than state-time, fixed effects. As noted in Section 3, I only have district identifiers for a subset of years, so these regressions use data between 1998 and 2009. Results remain very similar; several of the effects are actually strengthened, while the marginal cost and exit probability coefficients lose significance in the smaller sample.

Table 10.5: Input effects of China's WTO accession – state-district-time FEs

	MCs	Quality	Price	QAP	Quantity	Revenue	Exit
Panel A: Full Sample							
$InputTariff$	0.0897	0.292***	0.215***	-0.0729***	-0.0226	0.0885***	-0.00743
	(0.60)	(5.10)	(4.20)	(-4.40)	(-0.38)	(2.67)	(-0.75)
FEs	i,f,dt	i,f,dt	i,f,dt	i,f,dt	i,f,dt	i,f,dt	i,f,dt
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	19049	97629	97893	97629	97635	107680	107731
Panel B: Intensive Margin Only							
$InputTariff$	0.108	0.293***	0.218***	-0.0703***	-0.0328	0.0836**	-0.00480
	(0.71)	(5.12)	(4.26)	(-4.23)	(-0.55)	(2.53)	(-0.48)
FEs	i,f,dt	i,f,dt	i,f,dt	i,f,dt	i,f,dt	i,f,dt	i,f,dt
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	18519	94636	94898	94636	94641	104198	104248

Notes: t-statistics in parentheses. * p <0.10, ** p <0.05, *** p <0.01. Standard errors clustered at the firm level. All variables in logs, except *Exit* which is as described in Section 5.3. Panel A includes all products, while Panel B only includes those products which first appear in the dataset prior to China's WTO accession at the end of 2001. All regressions include firm, product and district-year FEs, and control for rural/urban location, public/private ownership, and the other four channels (direct import competition, output effects, export competition and export opportunities). Quality and quality-adjusted prices are calculated using the procedure of Khandelwal et al. (2013), and marginal costs are calculated using the procedure of De Loecker et al. (2016). The input channel is measured as described in Section 5.1 – i.e. each coefficient gives the percentage change in the average value of the outcome variable in the post-accession period resulting from a 1% higher average pre-accession tariff on the firm's inputs.

10.G Controlling for geographic collocation

This paper is focused on spillover effects through production linkages, yet geographic clustering could also play a similar role. Two industries which are closely connected in supply chains, e.g. iron foundries and industrial machinery manufacturing, may tend to locate close to one another to minimise transport costs or exploit other benefits of proximity. Locality-specific demand or supply effects could then correlate with input-output connections, biasing estimates of the true effect of the latter. Acemoglu, Akcigit & Kerr (2015, hereafter AAK) model local demand effects, such that, for instance, a negative shock to demand for cast iron has an adverse effect on all other industries in the region, within which industrial machinery may be over-represented. Such geographic collocation, if widespread, could lead to an overestimate of the importance of production linkages.

To control for such factors, I adopt AAK's empirical approach. This measures the contribution of this geographic overlay using the noncentred cross-region correlation coefficient of industries i and k, normalised by their national levels of production:[59]

$$geog_{ik} = \sum_{d} \frac{r_{d,i} r_{d,k}}{r_i r_d} \tag{10.2}$$

where $r_{d,i}$ is total sales of industry i in district d, and r_i and r_d are aggregates at the industry and district levels respectively.[60] As with equations 5.1 and 5.2, I then use these coefficients to take a weighted average of the import competition faced by geographically collocated industries – thus taking into account import competition effects through the geographic network, as distinct from the production network.[61]

Table 10.6 presents the results from including this collocation term in the main regressions. The results are very similar to those in Table 6.1 – collocation has only very minor effects on the coefficients, except for the product exit margin. This suggests that while local effects may impact profitability (for which the exit variable is a proxy, as in Section 4), they do not play a significant role in mediating the quality-upgrading mechanism. In other words, it is indeed input-output production linkages, rather than geographic collocation, that drive the upgrading effect.

[59] For a full derivation, see AAK sections II.B and III.C.

[60] As with the calculations of α_{ik} and γ_{ik} in Section 5, I use constant and predetermined coefficients throughout to prevent potential endogeneity of the geographic overlay with respect to tariff levels and/or trade flows. In this case, I use sales data from the year 2000 since this is the first year in which I have broad coverage across industry-district cells.

[61] Once again, I set $geog_{ii}$ equal to zero for all i to avoid double-counting the direct import competition channel.

Table 10.6: Input effects of China's WTO accession – including collocation

	MCs	Quality	Price	QAP	Quantity	Revenue	Exit
Panel A: Full Sample							
InputTariff	0.231*	0.234***	0.181***	-0.0498***	-0.0493	0.0751**	-0.00779
	(1.65)	(3.80)	(3.15)	(-2.99)	(-0.71)	(2.07)	(-0.77)
Collocation	0.414	0.0354	0.103	0.0631	-0.269	-0.0480	-0.117***
	(0.86)	(0.17)	(0.54)	(0.95)	(-1.08)	(-0.30)	(-2.92)
FEs	i,f,st	i,f,st	i,f,st	i,f,st	i,f,st	i,f,st	i,f,st
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	34401	164965	165533	164965	164971	175752	161038
Panel B: Intensive Margin Only							
InputTariff	0.248*	0.241***	0.188***	-0.0500***	-0.0565	0.0754**	-0.00646
	(1.75)	(3.94)	(3.27)	(-2.98)	(-0.81)	(2.10)	(-0.63)
Collocation	0.382	0.0117	0.0909	0.0786	-0.303	-0.0955	-0.113***
	(0.79)	(0.06)	(0.48)	(1.18)	(-1.21)	(-0.60)	(-2.81)
FEs	i,f,st	i,f,st	i,f,st	i,f,st	i,f,st	i,f,st	i,f,st
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	28460	137780	138229	137780	137785	147843	139739

Notes: t-statistics in parentheses. * p <0.10, ** p <0.05, *** p <0.01. Standard errors clustered at the firm level. All variables in logs, except *Exit* which is as described in Section 5.3. Panel A includes all products, while Panel B only includes those products which first appear in the dataset prior to China's WTO accession at the end of 2001. All regressions include firm, product and state-year FEs, and control for rural/urban location, public/private ownership, and the other four channels (direct import competition, output effects, export competition and export opportunities). Quality and quality-adjusted prices are calculated using the procedure of Khandelwal et al. (2013), and marginal costs are calculated using the procedure of De Loecker et al. (2016). The input channel is measured as described in Section 5.1 – i.e. each coefficient gives the percentage change in the average value of the outcome variable in the post-accession period resulting from a 1% higher average pre-accession tariff on the firm's inputs. Collocation is measured as described in Section 10.G, following Acemoglu, Akcigit & Kerr (2015): the interpretation of coefficients is analogous to that of the input channel, except with the average tariff calculation weighted by geographic correlation rather than input usage.

Table 10.7: Summary statistics by sector

NPCMS Section	**NPCMS Sector**	**Obs.**	**Fixed Assets (mean, INR million)**	**Employees (mean)**
Agriculture, Forestry, Fisheries	Products of agriculture, horticulture and market gardening	57	42	78
Beverages, Tobacco, Textiles	Beverages	2,668	327	488
	Grain mill products, starches and starch	3,194	131	189
	Knitted or crocheted fabrics; wearing apparel	4,393	98	378
	Leather and leather products; footwear	3,668	58	384
	Textile articles other than apparel	2,275	199	305
	Tobacco products	3,496	22	904
	Yarn and thread; woven and tufted textile fabrics	29,724	368	468
Metals, Machinery and Equipment	Basic metals	4,688	1290	550
	Electrical machinery and apparatus	9,705	195	330
	Fabricated metal products, except machinery and equipment	8,743	229	212
	General-purpose machinery	12,887	172	311
	Medical appliances, precision and optical instruments, watches and clocks	4,319	89	203
	Office, accounting and computing machine	8	20	122
	Radio, television and communication equipment and apparatus	887	423	350
	Special-purpose machinery	4,223	255	260
	Transport equipment	11,645	333	376
Other Transportable Goods	Basic chemicals	12,545	2220	424
	Furniture; other transportable goods n.e.c.	6,210	152	202
	Glass and glass products and other non-metallic products n.e.c.	3,621	313	275
	Other chemical products; man-made fibres	23,454	401	320
	Products of wood, cork, straw and plaiting materials	2,908	40	95
	Pulp, paper and paper products; printed matter and related articles	2,242	228	356
	Rubber and plastics products	21,008	212	194

Figure 10.1: Electric vehicle startup

Quality upgrade = lighter li-ion cells → lighter batteries, longer charge

Figure 10.2: Pharmaceuticals multi-national

Quality upgrade = fewer impurities in input chemicals → safer products

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