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Input reallocation within firms

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Input Reallocation Within Firms*

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Abstract This paper documents the within firm reallocation of inputs and outputs as a result of a trade policy shock on the input side. A unique firm-input level dataset for India with information on different raw material inputs used in production, enables us to identify firms with imported inputs subject to trade policy. To guide the empirics, we first develop a backbone model of heterogeneous firms that source inputs from abroad. We find that affected firms engage in input reallocation and lower their use of protected inputs by 25-40%, relative to other inputs. Especially large firms and multi-output firms skew their input use towards unprotected inputs. To identify the output reallocation ensuing trade protection on inputs, we develop a firm level input-output correspondence. Firms reduce their sales of outputs made of protected inputs on average by 50-80%, relative to sales of other outputs. We find a firm level decrease in markups, suggesting that the cost of imported inputs is only partially passed through to output prices. Thus, this paper documents a new channel through which trade protection negatively impacts input-using firms.

Keywords: Firm level data; Importers; India; Input Reallocation; Multi-product firms; Raw material inputs; Trade policy

JEL classification: F13; F14; L41; C23

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1 Introduction

In recent years, the number of papers in the trade literature on multi-product firms has been growing fast. Most papers thus far have focused on firms' output side. For example, Mayer, Melitz and Ottaviano (2014) show that a trade liberalization shock results in output reallocation, with firms selling relatively more of their core products. In their model, trade policy not just results in reallocation effects across firms (Melitz, 2003) but also generates reallocation across outputs within firms. Our paper studies the input side and shows that trade policy generates reallocation across raw material inputs within firms which subsequently translates in output reallocation away from products that use the protected inputs. While firms often use multiple raw material inputs in their production, expenses on these inputs are typically reported as one aggregate number at the firm level without any breakdown by input, such that input reallocation issues cannot be studied. Our paper makes use of a unique dataset of Indian firms with information on the quantity and value of each individual raw material input that a firm uses in its production. With these very disaggregate data, we are able to identify inputs such as "cotton yarn" and "nylon yarn", used in the production of shirts, and "caustic soda", used in the production of soap. The question we then ask is whether input tariffs cause a within firm reallocation of raw material inputs. We also link inputs affected by the trade policy to outputs sold by the firm. For this purpose, we construct a firm level input-output correspondence where we create a binary link between protected inputs and outputs that are produced with them. This allows us to examine whether the within firm reallocation of inputs induced by changes in input tariffs, also leads to a within firm reallocation of outputs.

To guide the empirics, we first develop a heterogeneous firm model with cost differences across outputs within a firm and with outputs using multiple raw material inputs in production. The model includes consumer preferences that allow for varying markups at the firm-output level and incomplete pass-through of costs into output prices (Melitz and Ottaviano, 2008). The model further allows for foreign raw material input use in production and imperfect substitution between foreign and domestic inputs, as in Halpern, Koren and Szeidl (2015) and Gopinath and Neiman (2014). But where these papers all consider single-output firms, we consider multi-output firms as in Eckel and Neary (2010). Firms have a core variety that is produced most efficiently and varieties away from the core are produced with a lower productivity. We show that the multi-output nature of firms allows for additional adjustment to trade policy shocks. The theory predicts within firm reallocation on the input and output side of firms subject to a trade policy shock on the input side at the firm-input level. Both in the theory and the empirics we leave aside industry level adjustments to trade policy shocks. Instead we focus on the within firm reallocation adjustments under trade policy to delineate our research question from earlier papers that mainly studied across-firm adjustments. Hence, our analysis conditions on firms being in the market before and after protection.

The trade shocks on the input side that we use to empirically test the predictions of the model, are Indian antidumping measures on the imports of narrowly defined raw material inputs used by Indian firms in production. We study all 500 Indian antidumping cases that were initiated between 1992 and 2007, each involving one or several products. In our data, we are able to identify about 1300 different firm-inputs that were subject to antidumping protection. India has become one of the heaviest users of antidumping measures worldwide, especially as of the early 2000s onwards (Bown and Tovar, 2011). These antidumping measures are in the vast majority of cases tariffs, similar to traditional product level import tariffs. Also, in more than 90% of Indian antidumping cases, the protected goods classify as inputs into production as opposed to final goods. Antidumping measures on a particular input are discriminatorily imposed against selected trading partners, but 86% of Indian antidumping cases cover at least one of the three most important source countries of imports, making it very likely for an Indian importer of affected inputs to be subject to these measures.

Empirically we find that firms affected by an adverse cost shock on the input side, reduce their use of protected inputs on average by 25-40%, vis-à-vis other inputs. This input reallocation then feeds into output reallocation with firms reallocating their sales towards outputs made of unprotected inputs, and reducing their sales of outputs made of protected inputs on average by 50-80%, vis-à-vis sales of other outputs. The input and output reallocation effects resulting from trade protection are most prominently present in firms that sell multiple products. The multi-output nature of firms reinforces the reallocation of resources towards unprotected inputs, in line with the theory. Empirically we also find that the input reallocation effect becomes larger the longer protection is in force.

Earlier papers have documented adjustments on either the input or the output side of the firm. Bernard, Redding and Schott (2011) and Eckel and Neary (2010) have shown how trade liberalization can induce firms to reduce their product scope and produce a smaller number of products. Goldberg, Khandelwal, Pavcnik and Topalova (2010a) document that trade liberalization results in newly imported intermediate inputs which triggers firms to extend product scope on the output side. Gopinath and Neiman (2014) document that within firm changes in the imported product mix constitute a significant channel of firms' adjustment in response to trade shocks. We differ from these papers by considering both the imported and non-imported inputs of a firm and how the relative share of inputs moves with trade policy. De Loecker, Goldberg, Khandelwal and Pavcnik (2016) study the effect of tariff liberalization on prices, marginal costs and markups at the firm-product level and find that trade liberalization raises firm-output level markups due to input tariffs falling stronger than output prices. While their paper is one of the few to stress the impact of trade policy through the input channel, they do not explore the within firm adjustment across inputs, like we do here. Where De Loecker et al. (2016) consider input tariffs at the industry level, we consider a trade policy shock at the narrow firm-input level corresponding with the product level detail in antidumping cases which typically corresponds to the HS 6-digit level. Also, De Loecker et al. (2016) use aggregate firm level data on raw material input expenditures, while we use a new dataset with firm-input level data on both value and quantity of each individual raw material input used by the firm in production. This disaggregation allows us to engage in a different research question, namely whether trade protection on inputs results in input and output reallocation within the firm.

Other papers that consider the link between input protection and output performance are amongst others Blonigen (2013) who finds that industrial protection in the steel sector has a negative impact on downstream manufacturing sectors of the country pursuing the industrial policy. Kasahara and Lapham (2013) use a structural firm level model and show that trade-restricting measures on imported intermediates lower aggregate industry-wide exports and productivity. But all these papers do not address the firm-product dimension and, therefore, do not consider within firm reallocation effects of trade policy, like we do here. While earlier empirical papers such as Konings and Vandenbussche (2008, 2013) and Pierce (2011), consider the effect of trade protection on import-competing firms, the focus here lies on firms that import the input but do not produce it themselves. Early theoretical work on the impact of trade policy already demonstrated the importance of firms' access to imported inputs for firm performance, where imported inputs can provide a channel for learning, access to new input varieties and inputs of higher quality (Ethier, 1982; Grossman and Helpman, 1991). By now there is a stock of empirical evidence confirming that trade shocks on the imports of intermediate inputs can have considerable effects on firm performance (Amiti and Konings, 2007; Kasahara and Rodrigue, 2008; Halpern, Koren and Szeidl, 2015).

An input-using domestic firm that is facing antidumping protection on raw material inputs has to decide whether to continue importing the input from the same supplier, to switch supplier or to stop using the input altogether. We argue here that whatever the domestic input-using firm is going to choose, its marginal cost of production is bound to rise. If the firm continues to import the input, it is forced to pay the tariff, which will raise the cost of the input. Alternatively, the domestic firm may switch away from the protected supplier and start sourcing the input from another foreign or domestic supplier. This supplier switching will involve an additional fixed cost as building new supplier relationships is time-consuming and costly. Additionally the production process needs to be adjusted to the alternative supplier's input variety. The inputs from the new supplier can be higher priced or can be of lower quality, which in case of the latter may cause additional processing costs for the input-using firm. Instead of disentangling each of the potential responses of domestic firms facing protected inputs, in the theory we focus on the common outcome which is that the marginal cost of the input that is sourced, goes up with the protection in either case. When the marginal cost of an input goes up, our model predicts that the firm moves away from that input. Empirically, we find that Indian firms do not so much drop imported inputs ensuing trade protection, but use less of them in production relative to other inputs, which is consistent with earlier findings on trade shocks and different adjustments along the margins (Das, Roberts and Tybout, 2007). The evidence suggests that at least part of the effect remains in place, once the temporary protection has been lifted, pointing to a more permanent effect of trade protection.

In the theory we decompose the input reallocation following trade protection into three different channels. First, input reallocation arises from "input substitutability". Given that inputs are imperfect substitutes in production, an increase in the cost of one input negatively affects firm demand for that input, but positively affects the demand for other inputs, for any given output quantity. Secondly, input reallocation results from a "quantity effect". Due to the trade shock, input costs rise and sales' prices for outputs, manufactured with the protected input, rise as well. This reduces the demand for the affected outputs which will further reduce the demand for protected raw material inputs and reinforce input usage away from the protected input. And thirdly, trade policy induces a "scope effect" on the output side of firms selling multiple products, with fewer output varieties using the protected input. As a tariff on foreign imports will raise the relative price of foreign inputs, this results in a relative increase in the demand for similar domestic inputs. Thus the model explains both within firm reallocation of raw material inputs and of outputs resulting from trade protection on the input side. Empirically we do not disentangle the different channels of input reallocation. For example, our data does not allows to identify the input-supplying firm, hence we do not observe whether an Indian firm switches away from a foreign to a domestic supplier of the same input. We only observe if the firm continues to use the affected input or not and how much of it. As such, we cannot directly observe the "scope effect" which in the theory we show to exist for multi-output firms that switch from a foreign input to a similar domestic input for some varieties. Indirectly, the empirical evidence does suggest that this "scope effect" is substantial, since in the data we find input reallocation to be much larger for multi-output firms than for single-output firms, suggesting that the third channel of adjustment in multi-output firms is an important one. What we measure in the data is the overall extent of input reallocation arising from any of the channels.

To empirically identify input reallocation, we use triple-difference regressions, which allow us to identify changes in the protected firm-input relative to every other individual firm-input used by the firm. More specifically, these regressions compare changes in treated firms' use of the protected input in quantities and values relative to other inputs within the importing firms, to changes in control firms' use of similar inputs relative to their other inputs (Ravaillon, Galasso, Lazo and Philipp, 2005; Frazer and Van Biesebroeck, 2010). We apply a linear estimator as well as a non-linear Poisson Pseudo Maximum Likelihood estimator (Santos Silva and Tenreyro, 2006), where the latter is increasingly used to address the zero value problem for dependent variables in regressions, which in our case arises from the possibility that firms drop or add inputs they use in production.

Our analysis is at the firm-input level. As a first control group we consider non-importers of the input that is mentioned in the antidumping case. But using non-importers can be problematic if they import affected inputs indirectly. In an alternative control group we do a matching between treated and untreated inputs at the firm-input level. In the matching, we verify that the treated inputs in treated firms are similar to the treated inputs in control firms. We consider them to be similar if they follow the same trend in input use in terms of quantity and value (which is at the firm-input level) and, at the same time, belong to importers operating in the same sector. Independently of the control groups used, we find significant changes in the evolution of protected inputs differing from the control group.

We find input prices of input-using firms that import the affected input to rise on average, compared to control firms, but only for small input-using firms. A potential explanation is that large firms, instead of continuing to import the protected input from the targeted trade partner and to pay the import duty, are more likely to switch away to a different foreign supplier or a domestic supplier of the same input. Given their firm size, large firms may be better placed to bargain over prices with the new supplier. Still, it is highly likely that even those firms for which we do not empirically observe a rise in their affected input prices, experience an increase in their marginal costs after the protection sets in. Their newly sourced input is of lower quality, thus raising the price-quality ratio, or is less compatible in later phases of the input-using firm's production process and subsequently result in higher marginal cost of outputs that are produced with the affected inputs. Therefore the maintained assumption in the theory model is that a duty on imported inputs raises the marginal cost even of those firms that switch suppliers.

By inserting firm-input fixed effects in the triple difference regressions, we account for observable and unobservable sources of heterogeneity at the firm-input level that may affect raw material input usage. Our purpose is not to explain input levels, which may largely differ between firms, but instead we study changes in input usage during the protection period. The main focus of our analysis thus lies on input reallocation. But for completeness we also identify outputs produced with affected inputs, and apply a separate triple-differencing approach on firm-outputs. As such, we identify a significant decrease in the affected firm-outputs relative to every other firm-output in treated firms compared to control firms

In the empirical analysis we address several endogeneity issues. First, we account for demand side shocks that could be correlated with the trade policy shock which is necessary to properly identify causality between the within firm adjustments and trade policy on the input side of a firm. We do so by eliminating firms that are selling products on the output side which are directly involved in antidumping cases. To clarify, when there is an antidumping case on the imports of "caustic soda", we exclude all Indian firms from our sample that produce caustic soda and whose sales of caustic soda may benefit from the import protection on foreign caustic soda. Still, there could be unobserved heterogeneity interfering with identification such as trade shocks coinciding with the antidumping protection. For this purpose we turn to Indian tariff data. We show that the trend in tariff reductions are similar for antidumping inputs than for other inputs during the protection period. A correct identification requires that inputs unaffected by the antidumping protection are not systematically different in the pattern of tariff liberalization, which we find to be the case.

A second source of endogeneity may arise due to political economy issues typically surrounding trade protection which may result in reverse causality. The government's decision to impose import protection is typically not random but the outcome of lobby efforts from firms . Given that we observe protection, this raises the question as to why input users do not oppose protection more (Grossman and Helpman, 1994). An important reason may lie in the legislation. Similar to many other antidumping laws in force worldwide, Indian antidumping legislation does not presribe the government to take into account interests other than those of the import-competing industry that produces a product similar to the protected one. While the political economy issues involved are likely to be important for import-competing firms, they will not explicitly be studied here. The assumption we maintain is that input-using firms do not lobby in favor of antidumping protection, as they are likely to be adversely affected by it.[1] By excluding import-competing firms protected by antidumping tariffs from our sample, the political economy concerns for our research question are less at play.

We also account for potential endogeneities arising from an anticipation effect. In anticipation of protection, input-using firms could already alter their behaviour prior to the protection decision. Therefore, in the empirics we allow for the possibility that input-using firm behavior may already change before the actual imposition of duties. Our results thus confirm the existence of an investigation effect (Staiger and Wolak, 1994), where firms already reduce their input use in anticipation of protection.

Finally, we also look into whether firm level markups are affected by trade protection. The theory model predicts a decline in markups induced by input and subsequent output reallocation. This is confirmed by the the empirical analysis, in which we measure markups at the firm level to take into account that markups of other products made by the firm could also be affected through linkages in supply and demand. Our evidence points in the direction of rising output prices of outputs produced with protected inputs. Despite rising output prices, we find trade protection on inputs to lower firm level markups which is consistent with De Loecker, Goldberg, Khandelwal and Pavcnik (2016) who find that trade liberalization raises markups. For the empirical estimation of markups we apply De Loecker and Warzynski (2012). Our finding that an adverse trade policy shock on inputs lowers markups for firms importing the input implies that the interests of input-using firms are hurt by trade protection. Thus, input reallocation documents a new channel through which trade protection negatively impacts input-using firms.

The remainder of this paper is organized as follows. The next section develops a relatively simple theory model which consists of multi-output firms that use multiple inputs. The model generates testable predictions on firm level input and output reallocation as well as on firm level markup changes in response to input tariffs. Section 3 describes the data and provides relevant descriptive statistics on Indian antidumping policy and Indian firms. Section 4 lays out the empirical identification strategy and engages in robustness checks. Section 5 develops a firm level input-output correspondence and relates input reallocation to output reallocation. Section 6 presents results on markups, and the final section concludes.

2 Theoretical Framework

To guide our empirical analysis, this section develops a back-bone multi-output firm model. Raw material inputs in production can be sourced domestically at a low fixed cost or from abroad at a high fixed cost. The benefit of sourcing from abroad is the lower cost per unit of input. As a result, the sourcing strategy of inputs will differ for varieties of different productivity within

[1] In fact, they tend to lobby against protection. See, for example, the newspaper articles published in *Times of India* on 17 January 2012 entitled *Weavers rue anti-dumping duty on nylon filament yarn*, and on 6 April 2009 entitled *Companies protest against proposed anti-dumping duty on steel.*

firms. A trade shock on raw material inputs in production, will lower the share of affected inputs in total firm input use and will also lower the share of output sales of the affected output in total firm output sales, which we define as input and output reallocation respectively.

2.1 Production Technology

Firms in an industry produce a continuum of differentiated varieties $s \in \mathcal{S}$. For each variety, the production function to produce quantity $q(s)$ of variety s is given as

$$q(s) = A(s)L^a M^b \tag{1}$$

where $A(s)$ is variety-specific productivity, L denotes labor and M denotes a composite material input used in production. The production function is characterized by the parameters $0 < a < 1$ and $0 < b < 1$ that give weights to each of the two factors of production. Similar to Halpern, Koren and Szeidl (2015) and Gopinath and Neiman (2014), we assume that the composite material input that is used in the production for a particular variety s is assembled as follows:

$$M = \left[x_1^{\frac{\theta-1}{\theta}} + x_2^{\frac{\theta-1}{\theta}} \right]^{\frac{\theta}{\theta-1}} \tag{2}$$

where x_1 and x_2 are quantities of two different raw material inputs, inputs 1 and 2. These inputs are imperfect substitutes in the production of M with θ being the elasticity of substitution.[2] Price p_L denotes the unit price of labour which is normalized to 1, and p_M denotes the price of one unit of the composite material input. Prices p_{x_1} and p_{x_2} are respectively the costs of using raw material inputs 1 and 2. The unit variable cost is constant within a variety s and equivalent to the marginal cost which can be written as

$$c(s) = \frac{1}{A(s)^{a+b}} \left(p_L \left[\frac{a p_M}{b p_L} \right]^{\frac{b}{a+b}} + p_M \left[\frac{b p_L}{a p_M} \right]^{\frac{a}{a+b}} \right) \tag{3}$$

and the effective price of the composite material input M can be derived as

$$p_M(p_{x_1}, p_{x_2}) = \left(p_{x_1}^{1-\theta} + p_{x_2}^{1-\theta} \right)^{\frac{1}{1-\theta}} \tag{4}$$

where firms act as price-takers on the input side.

Every variety s within the product market $\mathcal{S}$ can be characterized as a product i of firm j. We introduce subscript j to denote a firm and superscript i to denote a variety within a firm. Firms j differ in their productivity e.g. in the way they combine labor and the composite material input needed to produce $q_{ji}(s)$. Firms each have a core competence variety $i = 0$, and the productivity for this variety, $A_s = \delta^j$, is the highest within the firm. Firms can add varieties, but every added variety has a lower productivity than the core variety as productivity falls.

[2] Empirically, the elasticity of substitution between inputs can vary, but theoretically the result on within firm input reallocation does not depend on the particular value of θ, thus generating a flexible setup.

The variety-specific productivity parameter $A(s)$ equals

$$A_{ji}(s) = \alpha_{ji}(s) \tag{5}$$

with

$$\alpha_{ji}(s) = \delta_j - \eta \cdot i \tag{6}$$

where $\delta_j > 0$ is a firm-specific productivity parameter and $\eta > 0$ measures the incremental decrease in productivity for each additional variety i further from the core variety within the firm. Also note that the slope η does not vary by firm. Firm-product specific productivity, $\alpha_{ji}(s)$, is decreasing with the distance to the core competence variety, implying that the variety-specific productivity parameter $A_{ji}(s)$ decreases, the farther the variety is away from the firm's core variety.

2.2 Sourcing Material Inputs

Each variety i of firm j, uses two inputs in production which are imperfect substitutes. We assume that input 2 is a domestic input in production. It is important in the model that firms have at least one exclusively domestically sourced input that is not affected by eventual protection. This will allow us to study the implications of trade protection on input reallocation towards other inputs unaffected by the protection. Instead input 1 can be sourced either domestically and used in production at cost $p_{x_{1D}}$, or from abroad, implying a cost $p_{x_{1I}}$. The foreign material input x_1 is assumed to be cheaper such that $p_{x_{1I}} < p_{x_{1D}}$. Sourcing internationally however requires a larger fixed cost $F_{x_{1I}} > F_{x_{1D}}$, expressed in labor units.[3] The foreign and the domestically sourced input 1 are perfect substitutes, such that (2) remains unchanged, independent of the sourcing of input 1 but the price of the composite material input will differ depending on where input 1 is sourced from.

For an input-using firm, whether to source input 1 domestically or internationally, depends on the productivity of the output variety, $A_{ji}(s)$. For output varieties close to the core, productivity is high and less inputs are needed in production, whereas for distant varieties within the firm the reverse is true. Under domestic sourcing, the unit variable cost $c_{ji}(s)$ will be higher but fixed costs will be lower than under international sourcing.

2.3 Output Demand

Consumer preferences are defined over the continuum of differentiated varieties $s \in \mathcal{S}$. Following Ottaviano, Tabuchi and Thisse (2002) and Melitz and Ottaviano (2008), we assume preferences

[3] The lower price of the foreign input could also be modelled as a quality advantage in production as in Halpern, Koren and Szeidl (2015).

of a representative consumer to be given by a quadratic utility function denoted as:

$$U = \alpha \int_S q(s)ds - \frac{\beta}{2} \int_S [q(s)]^2 \, ds - \frac{\gamma}{2} \left[\int_S q(s)ds \right]^2 + q_0 \tag{7}$$

which gives rise to a linear inverse demand function

$$p(s) = \alpha - \beta q(s) - \gamma Q \tag{8}$$

where

$$Q = \int_S q(s)ds \tag{9}$$

denotes the aggregate industry output in product market $\mathcal{S}$, q_0 is the numeraire good and $\alpha > 0$, $\beta > 0$ and $\gamma > 0$ are the demand parameters. α captures the preference of the differentiated good with respect to the numeraire. β is the "love of variety" parameter, which induces consumers' preference towards the dispersed consumption of varieties.[4] Conditioning on β, γ expresses the degree of substitutability between varieties with a higher value indicating that varieties are closer substitutes. We develop the model under the assumption of a given number of firms, to abstain from entry and exit effects, as in Di Comite, Thisse and Vandenbussche (2014), but focus on the within firm adjustments. Varieties within a particular firm, belonging to product market $\mathcal{S}$, are equally good substitutes than other varieties within $\mathcal{S}$ belonging to different firms.

2.4 Market Equilibrium

Output price, output quantity and markups

The market for outputs $q(s)$ is characterized by monopolistic competition with every variety s being unique but individual firms being too small to influence market aggregates. Given that marginal costs are constant within each variety and there are no economies of scope in production, firms maximize profits by setting the optimal quantity and the optimal price for each of their varieties. Following Melitz and Ottaviano (2008), the equilibrium price, quantity, markup and profit of a variety s can then be derived as

$$p(s) = \frac{c_D + c(s)}{2} \tag{10}$$

$$q(s) = \frac{c_D - c(s)}{2\beta} \tag{11}$$

$$\mu(s) = \frac{c_D - c(s)}{2} \tag{12}$$

$$\pi(s) = \frac{(c_D - c(s))^2}{4\beta} \tag{13}$$

[4] Different from Ottaviano, Tabuchi and Thisse (2002), the parameter β used here captures the degree of horizontal differentiation net of the substitutability among varieties, as in for example, Di Comite, Thisse and Vandenbussche (2014).

where c_D is the cost of the firm who is just indifferent about remaining in the industry. It holds that $p(c_D) = c_D = p_{max}$ and firms do not make any profits at this choke price. It also holds that $q(c_D) = 0$, such that demand is driven down to zero.

Sourcing decision

For a given sourcing decision, every firm in the industry that uses a particular input pays the same price for that input. Unit variable costs for the output of each variety $q_{ji}(s)$ is assumed constant. Given the sourcing decision, variety level heterogeneity in marginal cost $c_{ji}(s)$ is solely determined by the productivity of variety s as shown in (3), where productivity and marginal cost are inversely correlated. As apparent from (10) and (11), marginal cost $c_{ji}(s)$ in turn determines $p_{ji}(s)$ and $q_{ji}(s)$. Thus, there is a unique correspondence between $A_{ji}(s)$ and $q_{ji}(s)$, where low productivity varieties within a firm have a high marginal cost, high output price and low sales $q_{ji}(s)$, whereas high productivity varieties have a low cost, low output price and high sales $q_{ji}(s)$.

For each variety i, a firm j will minimize total costs $TC_{ji}(s)$, given by:

$$TC_{ji}(m) = F_{x_{1I}} + c_{ji}(p_{x1I}, \vartheta) \cdot q_{ji}(m) \tag{14}$$

and

$$TC_{ji}(n) = F_{x_{1D}} + c_{ji}(p_{x1D}, \vartheta) \cdot q_{ji}(n) \tag{15}$$

where ϑ represents all the other variables affecting $c_{ji}(s)$ as shown in (3) which are the same for each variety, regardless of the sourcing decision. Recalling that $F_{x_{1I}} > F_{x_{1D}}$ and $p_{x_{1I}} < p_{x_{1D}}$, the intercept of (15) is smaller and the slope is steeper than that of (14), implying that cost curves intersect at a certain level of $q_{ji}(s)$. For varieties that sell in low quantities, minimizing total costs corresponds to maximizing the profits per variety for each variety, $\pi_{ji}(s)$. For low productivity varieties that sell in low quantities, it is most profitable for the firm to source input 1 domestically since this will minimize costs. We refer to these output varieties as type n varieties. But for high productivity varieties, sold in large quantities, international sourcing of input 1 will be cheaper. Those output varieties for which it is more profitable to source input 1 internationally are referred to as type m varieties.

Thus, for the multi-output firm, the total cost function can be described as the lower bound of the two cost curves such that $\widetilde{TC}_{ji}(s) = \min\{TC_{ji}(m), TC_{ji}(n)\}$. Varieties m, close to the core will pay a high fixed cost of sourcing input 1 from abroad but pay a low price for input 1, while varieties n, further away from the core variety, pay a lower fixed cost but face a higher marginal cost of sourcing input 1 domestically. For a multi-output firm to have both type m and type n varieties, the core productivity needs to be sufficiently high to allow the firm to source material inputs internationally for at least some of its output varieties. There will be a reallocation point, denoted by $\hat{i}$, which corresponds to the variety, where multi-output firms switch from international to domestic sourcing of input 1 in production, which is defined by the minimization of the total cost curve.

When we rank varieties by their cost, starting with the core variety, all varieties with a cost between the core variety and variety $\hat{i}$ will be of type m and source input 1 internationally, resulting in a total of m varieties that source input 1 from abroad. For the varieties that lie further from the core variety and with a cost higher than $\hat{i}$, domestic sourcing of input 1 is more profitable. To know exactly how many type n varieties the multi-output firm will produce, we need to determine the total output scope of the firm, which is what we do next.

Output scope

Total costs rise with every additional variety introduced in the multi-output firm and the profitability of each additional variety falls. The profits per variety are:

$$\pi_{ji}(s) = \max_{q_{ji}} \left[(p(s) - c(s)) \cdot q(s) - F \right] \tag{16}$$

where the fixed cost F, is the sourcing cost for input 1 e.g. either $F_{x_{1I}}$ or $F_{x_{1D}}$, depending on whether input 1 is sourced internationally or domestically. We summarize the set of products sold by the firm as total output scope, k, where the firm will sell all products that lie below the optimal output scope $k(j)$, $i \leq k(j)$.

Aggregating a firm's profit for each variety over the set of all offered products $i \in (0, k)$, firm j's total firm profit as a function of scope and profitability is defined as

$$\Pi(j, k) = \int_0^k \pi_{ji}(j, i) di \tag{17}$$

Taking the first derivative with respect to output scope k, yields the first-order condition

$$\frac{\partial \Pi(j, k)}{\partial k} = \int_0^k \frac{\partial \pi(j, i)}{\partial k} di + \underbrace{\pi(j, k(j))}_{\text{Marginal variety}} = 0 \tag{18}$$

Equation (18) implicitly defines the firm's optimal scope $k(j)$, given that the second-order condition is met.

Increasing scope, k, has no effect on the profitability of other varieties in the firm's portfolio, thus rendering the first derivative on the RHS of (18) equals zero. Hence, to guarantee that the first-order condition for profit maximization is zero, increasing scope will occur until the profit of the marginal variety equals zero. At variety $k(j)$, individual variety profits fall to zero which determine the optimal output scope for the firm. Once we determine optimal output scope $k(j)$, we can determine the range of type n varieties that lie between $\hat{i}$ and k, for which input 1 is sourced domestically.

2.5 Trade Policy

We now introduce trade protection into the model, which increases variable input costs and makes it more costly for the firm that produces type m varieties, to purchase input 1 internationally. Appendix A contains detailed proofs of the impact of trade protection on the different raw material inputs firms are using in production. Trade protection results in input reallocation away from the protected input, through three different channels: (1) input substitutability within a variety, (2) lower output demand for the product using the protected input, (3) a scope effect across varieties within the multi-output firm. We discuss each channel in turn.

Input substitutability within a variety

The first effect of raw material input reallocation arises from the substitutability of inputs 1 and 2 within the production of a variety of type m. When trade policy increases the cost of using the foreign sourced input $p_{x_{1I}}$, demand for this input x_{1I} goes down for a given output quantity $q_{ij}(s) = \bar{q}_{ij}(s)$ of variety s, such that $\frac{\partial x_{1I}(m)}{\partial p_{x_{1I}}}^{(1)} < 0$ where the superscript refers to channel 1 of input reallocation.[5] The demand for the imperfect substitute input 2 in a variety of type m for a given output quantity goes up as a result of trade protection, such that $\frac{\partial x_{2}(m)}{\partial p_{x_{1I}}}^{(1)} > 0$. The higher the elasticity of substitution θ between x_1 and x_2, the stronger the effect of input substitutability within a type m variety. For now, we assume the non-importer price $p_{x_{1D}}$ not to be affected by the protection thus trade policy will not affect input demand in type n varieties.[6] At the firm level, trade protection results in input reallocation e.g. it lowers the use of the protected input 1 in a firm's total input use.

Lower output demand within a variety

A second source of material input reallocation away from the protected input comes from the change in the quantity produced of the affected output. As apparent from (10) and (11), an increase in the variable cost of type m varieties will increase their price and reduce their quantity produced, $q_{ji}(m)$. This will decrease the demand for the composite material input used in the production of type m varieties and thus also the demand for both x_1 and x_2, such that $\frac{\partial x_{1I}(m)}{\partial p_{x_{1I}}}^{(2)} < 0$ and $\frac{\partial x_{2}(m)}{\partial p_{x_{1I}}}^{(2)} < 0$, where the superscript refers to channel 2 of input reallocation. These derivatives are conditional on input substitutability, discussed above. For type m varieties, lower output demand for affected varieties does not change the relative demand for the foreign input 1 relative to input 2, given that the composite material input is assembled with CRS, as apparent from (2). But at the firm level, input reallocation still occurs, since in the absence of demand spillovers between varieties of the multi-output firm, the demand for type n varieties is not affected. Thus the share of protected inputs in total inputs will fall further at the firm level through channel 2.

Scope across varieties

A third channel of input reallocation results from a change in the scope of varieties that sources the foreign input. For type m varieties, trade protection increases the slope of the total cost curve in (14) because of the higher variable sourcing cost of input 1 from abroad. This results

[5]We interpret $p_{x_{1I}}$ broadly as the cost of using the foreign sourced input 1, which aside from the price of the input may also include costs such as expenses on tariffs, processing costs or any other additional costs arising from a low quality of the input.

[6]In the empirics, we ensure that the results on input reallocation are not driven by a violation of this assumption.

in a new switching point $\hat{i}^\star$ between type m and type n varieties within the multi-output firm.[7] The firm reduces the number of type m varieties and increase the number of type n varieties but leaves total product scope $k = n + m$ unchanged. The reduction in type m varieties results in an additional decrease in the demand for protected inputs.

There will now be varieties w that switch their type from m to n. Before trade protection, these firms sourced input 1 internationally but they switch to the domestically sourced input 1 when trade protection is in place. For these varieties, input reallocation due to this scope effect is straight-forward to sign. Trade protection reduces the demand for input 1, in switching varieties w, such that $\frac{x_{1I}(w)}{\partial p_{x_{1I}}} < 0$, but increases demand for the domestically sourced input 1 in switching varieties w such that $\frac{x_{1D}(w)}{\partial p_{x_{1I}}} > 0$. Varieties that switch from type m to type n, will have higher output prices due to higher input costs and will sell less quantity than prior to the trade protection. Input 2 which is used jointly in production with input 1 will thus also be demanded less in the switching varieties, w, such that $\frac{\partial x_2(w)}{\partial p_{x_{1I}}} < 0$. In Appendix A we show that the net effect on the demand for foreign input 1 of this scope effect results in input reallocation e.g. a lower input use of the protected input in total input use at the firm level.

We can now pull strings together and formulate the following proposition which is the result of the three channels described above:

Proposition 1: Trade protection on imported raw material inputs, results in input reallocation with firms using less of the protected raw material input, relative to other raw material inputs in production (proof see Appendix A).

Next, we can show the following proposition.

Proposition 2: Trade protection on imported raw material inputs, results in output reallocation with firms producing less of the output affected by the protected input, relative to other outputs produced (proof see Appendix A).

The model also allows us to formulate a prediction on markups. At the variety level, markups decrease in $c_{ji}(s)$. So for type m varieties it holds that $\frac{\partial \mu(m)}{\partial p_{x_{1I}}} < 0$, while for type n varieties markups remain unchanged. For varieties w that switch, markups decrease as the variable cost in production goes up and pass-through in linear demand is incomplete. For the firm as a whole, the model thus predicts a decrease in markups, independent of the number of type m and type n varieties, which results in the following proposition.

Proposition 3: Trade protection on imported material inputs in production, results in a decrease of markups of affected outputs, which implies a decrease in firm level markups for firms that import protected inputs (proof see Appendix A).

[7] As long as the increase in costs induced by the tariff does not increase the international price above the domestic price, the most productive varieties that sell in high volumes, will continue to source from the targeted trade partner abroad. On high volumes, even a small cost difference can compensate for a higher fixed cost of sourcing from abroad.

3 Data

3.1 Indian Firm Level, Firm-input Level and Firm-output Level Data

To empirically test the propositions from the theory, this paper uses a unique firm-input level dataset with very disaggregate information on the value and quantity of the different raw material inputs that firms in India are using in production. The dataset allows us to distinguish between different narrowly defined inputs, which makes it particularly well-suited to investigate within firm reallocation effects across inputs. The firm-input level data are from a module of the *Prowess* database that to our knowledge has not been explored in the literature thus far. The database also has a module with firm-output level data on the value and quantity of different outputs sold and a module with firm level data from balance sheets and income statements of Indian firms. This paper takes advantage of all three modules.

The *Prowess* database is published by the *Centre for Monitoring the Indian Economy*, a private database provider based in Mumbai. The database includes information on medium- and large-size Indian firms, covering around 60-70% of organized industrial activity, 75% of all corporate taxes and more than 95% of excise duties collected by the Indian government (Goldberg, Khandelwal, Pavcnik and Topalova, 2010b). The period for which data are available to us is 1989-2007 with stronger data coverage as of the end of the 1990s. When a firm stops reporting, we cannot distinguish between a firm for which data are missing in the dataset and a firm that exits, making the data unsuited to study entry and exit of firms. Given the absence of small firms in the data, firm entry and exit is unlikely to be an important margin of adjustment in the event of firm-input protection. However, the data do allow us to study a more relevant extensive margin for our purposes which is adding and dropping of inputs for reporting firms.

Firm-input and firm-output level data that will be used to test propositions 1 and 2 are collected from manufacturing firms on the basis of the *1956 Companies Act*, which prescribes firms to report product level information on raw material input use and sales. Data on the input and output side are reported in terms of both values and quantities, where the physical unit in which quantity data are reported varies across firm-inputs and firm-outputs. The legislation does not prescribe firms to refer to any product code when reporting this information, but instead firms can report inputs and outputs by their name. To overcome this limitation, we develop a unique word-based algorithm, which will be discussed in section 4.1. The level of detail provided by firms is very disaggregate. We have data on 7625 firms with 19746 raw material input entries between 1989 and 2007, which is 2.6 entries per firm on average over the entire period. Out of these 7625 input-using firms, there are 6509 firms that also report data on sales quantities and values with 16016 output entries, which is 2.5 entries per firm on average. Most of the firms (58.5%) report to use more than one input. Most of the firms (56.0%) for which in addition product level sales information is available sell more than one product (Appendix Figure B1).

From the firm level data module in *Prowess*, we use the import value of raw materials and information on the main industry in which each firm operates, classified at the 5-digit level according to the National Industrial Classification (NIC), the industrial classification employed by Indian authorities. To test proposition 3, we also use firm level data on total raw material input expenses, salaries and wages, goods sales, power and fuel expenses and net tangible assets, and apply 2-digit sector level deflators to control for movements in factor prices.

3.2 Data on Indian Antidumping Policy

The World Bank's *Global Antidumping Database* (version *Q4_2011*) contains detailed information on Indian antidumping policy from 1992 onwards, when the first case was initiated in India, until 2012 (Bown, 2012). We added some information from original antidumping notifications published by the Indian government. The database contains information on the name and HS code of each product involved in an antidumping case (typically HS 6-digit level), the length of the protection spell, the antidumping tariff level when available, and the targeted trading partners. While we use the full database to provide descriptive statistics on Indian antidumping policy, the data are restricted to the 500 target-country-specific cases initiated between 1992 and 2007 for the regression analysis, in line with the data coverage available from the firm-input, firm-output and firm level database. Over 90% of these antidumping cases were initiated from the late 1990s onwards.

Indian antidumping policy is almost exclusively applied to inputs which are processed further in the production process (Appendix Figure B2). When classifying HS products along the Broad Economic Categories classification into inputs, capital goods and consumer goods, we find that 92.3% of affirmative rulings between 1991 and 2011 were about material inputs, which is more than is observed for other users of antidumping policy (Vandenbussche and Viegelahn, 2011). This focus of Indian antidumping policy on inputs therefore makes India a particularly relevant country to identify within firm reallocation effects of input tariffs.

The protected inputs most frequently belong to the chemical sector (44.8%), the plastics and rubber sector (16.5%), textiles (11.6%), machinery (11.2%) and base metals (9.2%) (Table B1).

4 Empirical Evidence on Input Reallocation

4.1 Identifying Treated Firm-inputs

To test proposition 1 on the within firm reallocation of inputs, we need to identify firm-inputs that are subject to antidumping measures, matching information on the products involved in antidumping cases with the firm-input level data. A serious limitation in the use of the Indian data is that firms are not legally obliged to use any product classification when reporting raw material inputs. For this reason, we develop a word-based algorithm designed to match the two databases by input name. The algorithm makes use of matching rules, specified for each individual antidumping case (see Appendix B.2). These matching rules search for combinations of words that describe the protected material input in the firm-input data. Through the algorithm we are able to identify 1133 firms that use an input that is at least once involved in an antidumping case between 1992 and 2007, corresponding to 1436 firm-input observations. Out of these 1133 firms, there are 989 firms that use an input at least once involved in an antidumping case where protection was imposed, corresponding to 1257 firm-inputs. In total 573 of these firms consume a positive amount of the input in the year the respective case is initiated, corresponding to 674 firm-input observations. For 434 of these firm-inputs, the firm also reports to be an importer of raw material inputs in the same year. We consider these firm-inputs as directly affected by antidumping protection, or as "treated".

We point out the possibility that some firm-inputs can falsely be counted as "treated", which may result in an underestimation of the policy impact we are trying to assess. The reason is that imports of raw material inputs are reported in our data only at the firm level, while antidumping measures are imposed against selected trading partners. Therefore we cannot exclude the possibility that importing firms do not import the input under protection, or import it from another country against which no antidumping measures are in force. To get an idea of the false treated we do the following. First, we turn to country-product level trade data from UN Comtrade and find that more than 86% of Indian antidumping cases target at least one and often more than one of the three most important trading partners for the given input, making it likely that importers of that input are indeed affected by antidumping protection. Second, it can be noted that among those firms that use an input on which antidumping measures are imposed, 65.5% are importers, compared to only 47.6% among those firms that do not use such an input. This statistically significant difference in importer shares indicates that the input on which antidumping measures are imposed is more likely to be imported by firms than other inputs.

We also account for demand side shocks that are likely to be correlated with the trade policy shock by eliminating firms from the analysis that are selling outputs directly involved in antidumping cases, which we identify by applying the word-based algorithm described above to the firm-output side. Especially in antidumping cases involving chemical and textile products, there are several incidences where products under antidumping protection are both inputs and outputs to the firm.

4.2 Testing for Within Firm Input Reallocation

Triple differencing

Under the assumptions we have made in the model, the use of input 1 relative to other inputs should reduce for importers, but remain constant for non-importers, when trade protection on input 1 comes into force. To test proposition 1, we employ a triple-difference regression at the firm-input level in which we compare how much importers switch from input 1 towards input 2, to how much non-importers of the same firm-input do. In this setup, importers are the treated firms, while non-importers form the group of control firms. While the extent to which importers switch inputs, and the extent to which non-importers do, can be estimated separately through two individual double-difference regressions, the triple-difference regression takes the difference between these two double-differences (Ravaillon, Galasso, Lazo and Philipp, 2005; Frazer and Van Biesebroeck, 2010):

$$[\Delta x_{1,j \in J_I} - \Delta x_{2,j \in J_I}] - [\Delta x_{1,j \in J_D} - \Delta x_{2,j \in J_D}] \tag{19}$$

where J_I are importers that source some of their inputs internationally, and J_D are non-importers that source all of their inputs domestically. Δ takes the difference between the input quantity during protection and the input quantity before protection and thus stands for a before-after comparison. Input quantities x_1 and x_2 are now expressed in logs.

The prediction of the model refers to input quantities, but empirically we also verify results for input values. Results for the share of the protected input in terms of value will be reported as a robustness check.[8]

J_I is the set of *treated firms*, which in the data are importers of raw material inputs that use an input on which antidumping protection is imposed in the year the antidumping case is initiated. These inputs are those that in the theoretical model correspond to input 1 with quantity $x_{1,j \in J_I}$ and can be labelled as *treated inputs in treated firms*.[9] Within the same importing firms, all other inputs correspond to input 2 with quantity $x_{2,j \in J_I}$ and can be labelled as *non-treated inputs in treated firms*. The theoretical model assumes that input 2 is always sourced domestically, while the data do not allow us to observe whether this is the case. However, as these inputs do not fall under antidumping protection, they can be part of the group of non-treated inputs in treated firms.

J_D is the set of *control firms*, which consists of those firms that consume an input on which antidumping protection is imposed, but are *not* importers of raw material inputs. These firms are not directly affected by antidumping protection, since they source all their inputs domestically. However, they are likely to be similar to treated firms as they use the same inputs. We will refer to these firms as *non-importer control group*. We then define as *treated inputs in control firms* those inputs that are consumed by these firms and put under antidumping protection, while we classify all other inputs consumed by the same firms as *non-treated inputs in control firms*.

To illustrate the triple difference setup and the use of four groups of inputs, consider the following example. Consider the antidumping case initiated by the Indian government in 2001 on Paracetamol, which results in a specific duty against China and Taiwan (China). In that case there is one particular pharmaceutical firm which is an importer of raw material inputs in 2001 and reports to use "Paracetamol" and "Acetic Anhydride" as input into its production. Another pharmaceutical firm does not import any of its inputs and uses "Paracetamol" as well as

[8] We can only define shares in values, since input quantities are often reported in different units.

[9] We only include firm-inputs into this group for which we observe exactly once within the data period a switch of the protection status from *no protection* to *protection*.

"Vitamine-E" in 2001. According to our definition of input groups, "Paracetamol" used by the importing firm belongs to the *treated inputs in treated firms* group, while "Paracetamol" used by the non-importing firm belongs to the *treated inputs in control firms* group. "Acetic Anhydride" used by the importer enters the *non-treated inputs in treated firms* group. "Vitamine-E" used by the non-importer is assigned to the *non-treated inputs in control firms* group. The triple-difference regression then estimates whether pharmaceutical firms that are importers (and hence are likely to be hurt by the antidumping measure) reallocate input expenditures away from "Paracetamol" to other inputs significantly more than non-importing users of "Paracetamol" (which are not directly affected by the measure) do.

Matched control group

Thus far we assumed that non-importers are not directly affected by the input protection. But there could be an indirect effect. Non-importers who purchase the protected input from domestic suppliers that import it from a country against which antidumping measures are in force, may be affected indirectly by the protection. There could also be other channels through which non-importers are affected such as price changes by domestic input producers or non-importers' adjustments of production in response to importers' reduction in the production of outputs made of protected inputs. To ensure that our results are not driven by these indirect effects, we construct an alternative control group. When results are qualitatively similar for this alternative control group, this ensures that indirect effects are not driving the results on input-reallocation.

This alternative control group consists of firms that have similar pre-treatment characteristics as the treated firms, as observed in the initiation year of the antidumping case, and use an input with similar trends in value and quantity as the treated input in treated firms. We also require the matched control firm-inputs to belong to firms that are from the same sector as the treated firm-inputs. Additionally we now also require that the matched control firm is an importing firm at the time of the antidumping initiation. This group of firm-inputs will be referred to as *matched control group*, where we apply *exact matching* techniques to match each treated firm-input to four control firm-inputs with *exactly* the same characteristics.

This implies that, for each treated firm-input observations in the antidumping case initiation year, we select so-called "twins", which are control firm-input observations in the same year that belong to firms that are importers, operate in the same NIC 2-digit sector as the treated firm, and are not affected by antidumping protection (neither on the input nor on the output side). Moreover, we categorize firm-inputs according to their pre-treatment value into four quantiles, which approximately correspond to *strongly growing*, *weakly growing*, *weakly declining* and *strongly declining* input use in terms of value. We impose that the trend in the input value of control firm-inputs falls into the same category as the trend in the input value of treated firm-inputs. The same procedure is undertaken to ensure that control and treated firm-inputs follow a similar trend in terms of quantity. Out of the typically few firm-inputs that fulfill the conditions that we impose, four firm-inputs are chosen randomly that have not yet been selected to be "twin" for other treated firm-inputs. These firm-inputs will be referred to as *treated inputs* *in control firms*, while all other inputs used by the same firms are *non-treated inputs in control firms*.

Identification

To identify the causal impact of antidumping protection on firms' input use, we need to account for input or output shocks that might be correlated with India's use of antidumping protection. One major concern might be the possible correlation between India's trade liberalization and its use of antidumping protection (Bown and Tovar, 2011). Trade liberalization could potentially bias our identification, if inputs under antidumping protection are affected differently by the trade liberalization than other inputs.

We document the evolution of average applied MFN tariffs in 1996-2007 (the period for which tariff data are available for India from the WTO's *Integrated Database*) which covers the period in which almost all Indian antidumping cases until 2007 have been initiated (Appendix Figure B3). The averages are calculated for chemicals, rubber and plastics, textiles, machinery and base metals which together account for the vast majority of Indian AD cases (Table B1), distinguishing between products involved in antidumping cases for which antidumping protection is granted and all other products. Figure B3 demonstrates that MFN tariffs for these two types of products have gradually declined in an almost parallel fashion over time. This result suggests that products that fall under antidumping protection are on average not differently affected by India's trade liberalization than other products in the period under consideration. The above is reassuring and suggests that tariff liberalization is not systematically different for antidumping inputs than for others. Also, since most of our observations on antidumping protection are from the late 1990s onwards, while trade liberalization mainly occurred in the early 1990s, this further reduces the coinciding of antidumping tariffs with tariff cuts.

4.3 Estimation Methodology

The estimation methodology that we apply to the triple-difference regressions needs to account for the fact that around 14% of non-missing firm-input values and quantities in our data are zero. A zero appears when an input is not reported to be used in a particular year, while we find it to be used in another year. At the same time, we need to estimate an equation, in which input value or quantity as dependent variable appear in logarithmic form, with firm-input fixed effects included as independent variables. For these reasons, we employ the Poisson Pseudo Maximum Likelihood (PPML) estimator with firm-input fixed effects (Santos Silva and Tenreyro, 2006; Wooldridge, 2002). Non-linear estimation with PPML has the advantage that input values and quantities enter the regression directly as levels rather than in logarithmic form. As a consequence, zeros do not drop out, but coefficients can still be interpreted as in a standard semi-logarithmic regression.

The triple difference regression in (20) is estimated with PPML on the four groups of firm-inputs, used by treated and control firms, and takes the following form:

$$
\begin{aligned}
IN_{ijt} = \exp\Big(&\alpha + B\,(Pre\_AD_{ijt} \times TR_{ij} \times T_i) + \beta\,(AD_{ijt} \times TR_{ij} \times T_i) + b\,(Post\_AD_{ijt} \times TR_{ij} \times T_i) \\
&+ C\,(Pre\_AD_{ijt} \times T_i) + \gamma\,(AD_{ijt} \times T_i) + c\,(Post\_AD_{ijt} \times T_i) \\
&+ F\,(Pre\_AD_{ijt} \times TR_{ij}) + \phi\,(AD_{ijt} \times TR_{ij}) + f\,(Post\_AD_{ijt} \times TR_{ij}) \\
&+ M\,(Pre\_AD_{ijt}) + \mu\,(AD_{ijt}) + m\,(Post\_AD_{ijt}) + \epsilon_t + \epsilon_{ij}\Big)\epsilon_{ijt}.
\end{aligned} \tag{20}
$$

where the dependent variable IN_{ijt} refers to either the quantity or the value of raw material input j used by firm i in year t. The equation includes year fixed effects ϵ_t, firm-input fixed effects ϵ_{ij} and the error term ϵ_{ijt}. Inserting firm-input fixed effects in the regressions also controls for unobserved time-invariant heterogeneity between firms.

The triple-difference setup requires the inclusion of interactions of three different dummy variables. AD_{ijt} marks the years of antidumping protection for all four groups of firm-inputs.[10] We consider a year as *treatment year* if an antidumping measure has been in force for at least six months. T_i is firm-specific and identifies all firm-inputs that are used by treated firms. TR_{ij} marks treated inputs in both treated and control firms.

We also allow for an investigation effect by including interaction terms with Pre_AD_{ijt}, a pre-treatment dummy variable that marks the year before protection is in force, which is typically the year in which the antidumping case is initiated. This accounts for the possibility that firms adjust their input use already prior to protection, in anticipation of an antidumping measure coming into force. Similarly, we allow for post-treatment effects by including interaction terms with $Post\_AD_{ijt}$, a post-treatment dummy variable which marks the years after treatment. This allows us to test whether the impact of protection remains in place, even after the antidumping measure is lifted. In equation (20), we denote coefficients in upper-case letters to indicate investigation effects (Pre_AD_{ijt}), in Greek letters to indicate actual protection effects (AD_{ijt}), and in lower-case letters to indicate post-treatment effects ($Post\_AD_{ijt}$).

In this triple-difference setup, ϕ measures input reallocation from treated towards non-treated inputs within control firms, and $\phi + \beta$ is a measure for input reallocation from treated towards non-treated inputs within treated firms. Hence, β corresponds to the difference specified in (19) and measures the differential impact that trade protection has within treated firms vis-a-vis control firms. In other words, if β is significantly negative, trade protection causes firms to engage in input reallocation towards the non-protected input. In analogy, B is the anticipation effect and b stands for the post-treatment effect.

4.4 Main Results on Input Reallocation

Table 1 reports results of the triple-difference regression specified in equation (20) on the sample of multi-input firms. Columns 1-4 show results on input value and quantity when using non-importers as a control group, while columns 5-8 show the results for matched firms as control

[10] When more than one raw material input within a firm falls under protection, AD_{ijt} is one for non-treated inputs whenever *at least one* antidumping measure is in place on a treated input used by the firm.

group. For each control group, regression results are shown with and without allowing for an effect in the year before the protection comes into force. Indian antidumping investigations typically last several months up to a year before a final decision on the case is taken. We test whether a within firm reallocation of inputs already takes place within this year. To deal with potential heteroskedasticity and serial correlation, we report standard errors clustered at the firm-input level. Given that we have a relatively large number of groups within the panel, we also computed block-bootstrapped standard errors to deal with serial correlation, as recommended by Bertrand, Duflo and Mullainathan (2004). Block-bootstrapped standard errors gave us quite similar results as clustered standard errors, and will not be reported for brevity.

The evidence in Table 1 confirms proposition 1 derived in the theoretical model and shows that treated firms lower the use of treated relative to non-treated inputs, more than control firms do in response to antidumping protection. Importing firms engage in a within firm input reallocation and skew their input use towards unprotected inputs when faced with trade protection. Estimates for the differential impact (β) show the expected negative sign and are significant in every specification that uses the input value as dependent variable. Similarly, the impact on input quantities is estimated to be significant or very close to significant.[11] The magnitudes of the estimated coefficients imply that firms reduce their use of protected inputs by 25-40% on average, relative to other inputs, in response to trade protection.[12]

The point estimates for input values and input quantities are similar, suggesting that input prices on average remain unchanged. Given that firms are not required to include tariff expenditures when reporting their consumption of material inputs, input prices in our data are reported net of tariffs and hence do not include the cost increase related to antidumping tariffs. Not just tariffs but also switching suppliers is likely to result in additional variable costs further down the production process of input-using firms when inputs are either of lower quality or have lower compatibility with other inputs than before the protection. Therefore, the relative stability of input prices observed in the data does not contradict an increase in the cost of using affected inputs as assumed in the theory. In the theory, $p_{x_{1I}}$ reflects the *cost of using the foreign input 1* which includes more than just the purchase price of input 1. In the input price data however, we do not observe the *cost of using* input 1, but only the input purchase price which is not very informative of the cost associated with using a protected input for reasons outlined above. While costs of using the protected input are likely to go up, the impact of trade protection on the observed purchase price of the input is ex-ante unclear. On average we find that input purchase prices do not appear to change, but when decomposing the average input price effect and split firms according to the intensity of use in the use of affected inputs, we find that low intensive input users face an increase in average input prices of protected inputs.[13]

[11] Coefficients in regression models that make use of quantity data are typically estimated with a lower degree of precision so that statistical significance is harder to obtain, given that data on physical quantities is naturally more prone to measurement error than data on values.

[12] The impact can be calculated as $(\exp(\beta) - 1) * 100$ in %, where β is the estimated coefficient. For example, the estimated coefficient -0.461 in column (1) of Table 1 translates into an impact of -36.9%.

[13] The relative stability of input purchase prices in antidumping cases has also been found by others (Konings and Vandenbussche, 2005). One potential explanation is that the antidumping law rules out absorption, implying that trading partners subject to import tariffs cannot lower their f.o.b. border prices during protection which

Table 1: Main results on input reallocation

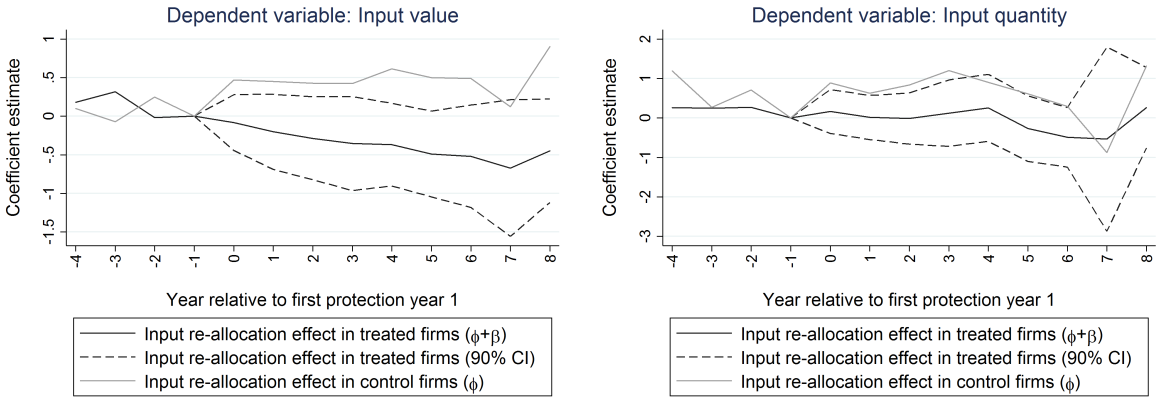
Dependent variable: Raw material input use (firm-input level)								
	Control firms: Non-importers				Control firms: Matched			
	Value	Quantity	Value	Quantity	Value	Quantity	Value	Quantity
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Pre AD x TR x T (B)			**-0.466****	**-0.689**			**-0.054**	**0.263**
			(0.199)	**(0.487)**			**(0.116)**	**(0.286)**
Pre AD x T (C)			0.354**	0.774**			0.031	-0.028
			(0.161)	(0.326)			(0.092)	(0.164)
Pre AD x TR (F)			0.353***	0.627			0.047	-0.262
			(0.123)	(0.450)			(0.076)	(0.189)
Pre AD (M)			-0.338***	-0.480			-0.020	0.150
			(0.111)	(0.303)			(0.048)	(0.112)
AD x TR x T (β)	**-0.461***	**-0.389***	**-0.605****	**-0.582**	**-0.343*****	**-0.536**	**-0.360****	**-0.466**
	(0.242)	**(0.214)**	**(0.293)**	**(0.371)**	**(0.132)**	**(0.360)**	**(0.148)**	**(0.330)**
AD x T (γ)	0.349***	0.876***	0.449***	1.108***	0.082	0.030	0.093	0.039
	(0.112)	(0.231)	(0.159)	(0.291)	(0.079)	(0.082)	(0.106)	(0.120)
AD x TR (ϕ)	0.129	0.209	0.222	0.381	0.033	0.517	0.047	0.447
	(0.206)	(0.190)	(0.235)	(0.346)	(0.092)	(0.318)	(0.105)	(0.289)
AD (μ)	-0.299***	-0.518***	-0.399***	-0.648**	-0.092*	-0.158*	-0.098	-0.096
	(0.103)	(0.199)	(0.131)	(0.286)	(0.053)	(0.083)	(0.065)	(0.071)
Post AD x TR x T (b)	**-1.033*****	**-0.699***	**-1.244*****	**-1.160***	**-0.441**	**-0.753****	**-0.459**	**-0.660***
	(0.307)	**(0.420)**	**(0.371)**	**(0.615)**	**(0.304)**	**(0.372)**	**(0.312)**	**(0.342)**
Post AD x T (c)	0.603***	0.086	0.666***	0.314	0.243	0.021	0.250	0.037
	(0.131)	(0.454)	(0.157)	(0.483)	(0.231)	(0.149)	(0.240)	(0.165)
Post AD x TR (f)	0.583**	0.926***	0.742**	1.345**	-0.023	0.664**	-0.007	0.581**
	(0.234)	(0.250)	(0.292)	(0.541)	(0.205)	(0.283)	(0.215)	(0.248)
Post AD (m)	-0.654***	-0.342	-0.716***	-0.471	-0.377*	-0.241**	-0.380*	-0.182*
	(0.109)	(0.222)	(0.121)	(0.310)	(0.204)	(0.100)	(0.202)	(0.101)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm-input FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of firm-inputs	982	957	982	957	1303	1264	1303	1264
Number of observations	8025	7808	8025	7808	11240	10926	11240	10926

Notes: ***, ** and * indicate a significance level of 1, 5 and 10%, respectively. Reported standard errors in brackets are cluster robust with clustering at the firm-input level. The table shows results of the regression described by equation (20), estimated with PPML on the sample of multi-input firms, using raw material input value or quantity (at the firm-input level) as the dependent variable. *TR* marks treated inputs in both treated and control firms, *T* identifies all firm-inputs that are used by treated firms, *Pre AD* marks the year before protection is in force, *AD* marks the years of antidumping protection, and *Post AD* marks the years after treatment. Average (pre- & post-)treatment effect on the treated is in bold with β (B & b) as our main coefficient of interest.

Table 1 also confirm the existence of an investigation effect (β), where firms already reduce their input use in the year before trade protection is in force (Staiger and Wolak, 1994). Similarly, results also point to a post-treatment effect, indicating that firms do not (or at least not fully) change back to their pre-protection input allocation, once protection has expired. This implies that antidumping measures have a permanent impact on firms' input use, despite their temporary nature.

would render the protection ineffective.

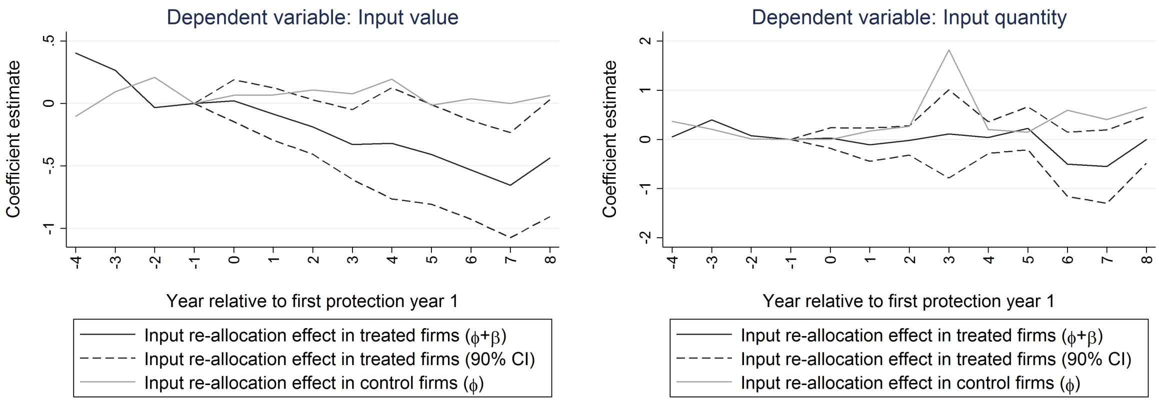
Figure 1: Comparison of input reallocation between treated and non-importing (control) firms



Source: Authors' estimates.

Notes: Estimates are based on the regression described by equation (20), but distinguishing between different years of protection instead of estimating an overall effect of protection. The equation is estimated at the firm-input level with PPML and using raw material input value or quantity (at the firm-input level) as the dependent variable. Year 1 is the year in which protection is in force for the first year and years on the horizontal axis are relative to that year. Year -4 refers to five or more years before protection is imposed. Year 7 refers to seven or more years of protection in force. Year 8 refers to years after the expiry of protection. CI stands for the confidence interval.

Figure 2: Comparison of input reallocation between treated and matched (control) firms



Source: Authors' estimates.

Notes: See Figure 1.

In Figures 1 and 2, we visualize the dynamics of the impact of trade protection over time on input values (left-hand panel) and quantities (right-hand panel), using non-importers and matched firms respectively as a control group. For this, we estimate equation (20), but replace the single protection period dummy AD_{ijt} by annual protection dummies for each of the years ensuing protection. Similarly, we also test for an impact in each of the individual years before protection is imposed. This way we can verify that treated and control firms are on a common trend regarding input reallocation before protection.

The horizontal axis is normalized such that year 1 corresponds to the first year of protection. Any anticipation effect would then show up in year 0, the year before protection is in place. Estimates are to be interpreted as relative to year -1. If the *input reallocation effect in control firms* (solid gray line, ϕ) is negative, control firms switch on average from treated towards non-treated firm-inputs. If the *input reallocation effect in treated firms* (solid black line, $\phi + \beta$) is negative, treated firms do. We also contruct a confidence interval (dashed black line) in which we consider the standard error of the estimate for the differential impact (β), in order to detect significant differences between input reallocation in treated and control firms.

The figures show that treated and untreated firms have common trends in input use prior to protection. They also confirm the existence of an anticipation effect but not earlier than in year 0. In year 0 and from year 1 onwards, when protection is in force, the *input reallocation effect in control firms* typically lies above or just marginally within the 90% confidence interval for the *input reallocation effect in treated firms.* This strongly points to a causal negative impact of antidumping on the use of protected inputs vis-a-vis other inputs. The dynamics over time suggests that the impact tends to become stronger the longer protection is in place. Moreover, input reallocation remains in place even after protection expires.

4.5 Additional Results on Input Reallocation

Results for single- and multi-output firms

Next, we show results separately for single- and multi-output firms (Appendix Table C1). A priori we would expect input reallocation to be easier for multi-output firms, given that these firms are in a better position to reallocate resources across product lines. This would also be in line with the theoretical model, which shows that trade protection affects the quantities of different inputs used by firms through three different channels. Input substitutability within a variety (1) will lead to a within firm input reallocation in both multi-output firms and single-output firms. Lower output demand within a variety (2) will equally lead to input reallocation in multi-output firms. However, it will not lead to input reallocation in single-output firms, but will in the presence of CRS leave the relative share of each individual input in firms' overall input consumption unchanged. Similarly, the scope effect across varieties (3) only occurs for multi-output firms, not for single-output firms.

Results confirm that input reallocation is stronger in firms that sell multiple products. While we find a significant negative impact on both quantities and values for multi-output firms, only quantities go down for single-output firms. Moreover, the estimated magnitudes of the effect are larger for multi-output firms.[14]

[14] This result is also in line with the results of Lu, Tao and Zhang (2013) who find that, Chinese single-output firms are more likely to exit the US market in response to US antidumping measures than Chinese multi-output firms that can shift resources towards products not affected by the US import measures.

Results by firm size

We then verify results along the firm size dimension, where firm size is measured in terms of net fixed assets in the year the antidumping case is initiated (Table C2). Larger firms typically produce more products (Bernard, Redding and Schott, 2011), hence it may be easier for them to switch inputs and shift resources across different product lines. In addition, large firms tend to be less financially constrained and can more easily invest into tangible assets which may be necessary to boost certain product lines not dependent or less so on the protected input (Manova and Yu, 2012). In Table C2, we show results for small and large firms, defined as firms below or above the median size, respectively.

Results suggest that it is mostly large firms that are driving the results on input reallocation obtained in the full sample. While the coefficient on input reallocation is negative for both types of firms, it is only significant for the larger firms. Thus, firm size appears to be an important determinant of how much importers skew their input use towards unprotected inputs as a response to trade protection.

Result by share of inputs under protection

We also verify results for the intensity at which firms use the protected input (Table C3). It turns out that as soon as the share of the protected input in the total value of inputs used by firms falls below 20%, input reallocation can still be observed on input quantities but no longer on input values, pointing to an increase in the average input price for these low intensive users.

A likely explanation is that intensive users of the protected input are in a better position to influence the price at which the input is supplied by the new supplier, in case they decide to switch supplier. Less intensive input users are less able to influence the conditions at which the input is supplied by the new supplier. As a result, while these less intensive input users also reduce their consumption in quantities of protected inputs, they are not able to reduce the corresponding input expenses. In contrast, intensive users of the input, reduce their input consumption both in terms of values and quantities.

Results by sector

Finally, we report results for subsamples that include or exclude firms from certain sectors (Table C4). Only for the chemicals sector, the sample is sufficiently large to run sector-specific regressions, given that more than one third of the input users affected by antidumping protection are operating in this sector. However, we also run regressions, after dropping firms from a particular sector from the sample. One-by-one we exclude firms that operate in the chemicals, rubber and plastics, basic metals and textiles sector, which are the sectors most frequently affected by antidumping on the input side. Finally, we also run regressions on a sample that exclusively consists of firms from these four sectors, excluding all other sectors.

The estimated impact on matched firms is very similar across all subsamples, indicating that it is not one particular sector that is driving the results. β is always estimated to be negative and the impact of trade protection remains significant with regards to the input value for almost all samples considered. For quantities, results are typically either significant or very close to significance, which confirms earlier results obtained for the full sample. Therefore, it is safe to state that input reallocation in response to trade protection is not a sector-specific phenomenon.

4.6 Robustness Checks on Input Reallocation

In this section, we report results when using the value share of each protected input in total firm inputs as a dependent variable, instead of using input quantity (value) at the firm-input level as a dependent variable. Given that other non-treated inputs are directly embedded into the denominator of the dependent variable and do not appear as separate observations, we now use double-difference regressions. In the double-differencing, we compare the evolution of the firm-input level share of each protected input before and after protection within treated firms to the evolution of the corresponding share within non-importing and matched control firms, using a linear panel firm-input fixed effects estimator. These shares can only be calculated for input values but not for input quantities, since inputs in the data are often reported in different physical units, making it impossible to add or compare across units.

The results we obtain from the double differencing on the share of protected inputs in total inputs in Table 2, shed a different light on the triple differencing PPML results that we obtained earlier in Table 1. Based on the coefficients in Table 1, we reported a 25-40% reduction in the quantity/value of a protected input, relative to unaffected inputs, which may have appeared large. However, our results on the shares as reported in Table 2 confirm these earlier results. Based on Table 2 coefficients, we find that trade protection reduces the firm-input share of a protected input in firms' total input value by around 4-5 percentage points on average for the full sample (β). The impact is estimated to be around 8 percentage points for non-chemical firms. These results on the shares are in line with the triple-differencing PPML results reported in Table 1 earlier. To see this, consider as example a hypothetical firm that uses three inputs in its production and all of these three inputs have the same value before protection. A percentage reduction by 25% of one of the inputs as a result of protection (which is in the range of the PPML estimates reported in Table 1), then translates into a decrease in the share of the input value under protection by 6 percentage points (which is in the range of estimates reported in Table 2).[15]

[15]Before trade protection, each input's share in the total input value used by the firm is $\frac{1}{1+1+1} = 33.3\%$. With trade protection, this share becomes $\frac{(1-0.25)}{1+1+(1-0.25)} = 27.3\%$ for the protected input.

Table 2: Robustness check on input reallocation, using the share of input value under protection as dependent variable

Dependent variable: Share of input value under protection (firm-input level)				
	All	Non-Chemicals	All	Non-Chemicals
	Control firms: Non-importers		Control firms: Matched	
	(1)	(2)	(3)	(4)
Pre AD x T (B)	**-0.036**	**-0.053**	**-0.028****	**-0.041****
	(0.026)	**(0.032)**	**(0.012)**	**(0.017)**
Pre AD (C)	0.024	0.035	0.004	0.009
	(0.023)	(0.030)	(0.007)	(0.009)
AD x T (β)	**-0.044**	**-0.079****	**-0.048*****	**-0.083*****
	(0.028)	**(0.035)**	**(0.017)**	**(0.024)**
AD (γ)	0.014	0.030	-0.000	0.014
	(0.024)	(0.033)	(0.011)	(0.017)
Post AD x T (b)	**-0.080**	**-0.116****	**-0.036**	**-0.055***
	(0.049)	**(0.053)**	**(0.028)**	**(0.029)**
Post AD (c)	0.049	0.076	-0.021	0.021
	(0.046)	(0.054)	(0.024)	(0.032)
Year FE	Yes	Yes	Yes	Yes
Firm-input FE	Yes	Yes	Yes	Yes
Number of firm-inputs	269	154	475	243
Number of observations	2131	1256	3996	2096

Notes: ***, ** and * indicate a significance level of 1, 5 and 10%, respectively. Reported standard errors in brackets are cluster robust with clustering at the firm-input level. Average (pre- & post-)treatment effect on the treated is in bold with β (B & b) as our main coefficient of interest. Reported results are based on the following equation, estimated in a double-difference regression and using a linear panel firm-input fixed effects estimator: $SH_{ijt} = \alpha + B\,(Pre\_AD_{ijt} \times T_i) + \beta\,(AD_{ijt} \times T_i) + b\,(Post\_AD_{ijt} \times T_i) + C\,(Pre\_AD_{ijt}) + \gamma\,(AD_{ijt}) + c\,(Post\_AD_{ijt}) + \epsilon_t + \epsilon_{ij} + \epsilon_{ijt}$. SH stands for the input value of a particular input, falling under protection, as a share of total inputs used by the firm. T is a dummy variable that marks treated firms. AD is a dummy variable that marks the period of protection. *Pre AD* and *Post AD* are dummy variables defined as in equation (20), marking respectively the year before protection is imposed and the years after protection has expired.

As further robustness checks, we also experimented with using a linear panel firm-input fixed effects estimator instead of PPML to estimate the triple-difference equation (20), now using the logarithm of input value and quantity as dependent variables. This implies that observations where the input value or quantity as dependent variables is zero, drop out of the regression. In addition, we estimated the triple-difference equation (20) with PPML, but replacing the protection dummies with measures of the magnitude of protection such as tariffs. In both cases, we obtained similar results as before, confirming input reallocation within importers.

4.7 Extensive Margin Effects on Input Reallocation

The adjustments that we have documented up to this point could be driven by both the extensive margin of input use (whether firms use the protected input or not) or the intensive margin of input use (how much firms use of the protected input in quantity and value). The evidence discussed thus far already suggests that most of the adjustment comes from the intensive margins, since when dropping the zeros from the dataset, we still find an effect of trade protection (see section 4.6). But it is clear that firms can also adjust the *extensive margin* and decide whether to start using an input that was not used before or whether to drop an input during protection. While the extensive margin of firm entry and exit cannot be studied with our data, we can study the extensive margin of adding and dropping inputs.

We construct a categorical variable at the firm-input level that indicates whether firms drop an input, add a new input, or leave the input use unchanged. This categorical variable is then used as a dependent variable in a multinomial regression, which is otherwise is similar to (20):

$$\begin{aligned}
Pr(drop) &= \frac{exp(X\beta_1)}{1+\sum_{k=1}^{2} exp(X\beta_k)} \\
Pr(add) &= \frac{exp(X\beta_2)}{1+\sum_{k=1}^{2} exp(X\beta_k)} \\
Pr(unchanged) &= \frac{1}{1+\sum_{k=1}^{2} exp(X\beta_k)}
\end{aligned}$$

with

$$\begin{aligned}
X\beta_k = \beta_{0k} &+ \beta_{1k}Pre_AD_{ijt} \times TR_{ij} \times T_i + \beta_{2k}AD_{ijt} \times TR_{ij} \times T_i + \beta_{3k}Post_AD_{ijt} \times TR_{ij} \times T_i \\
&+ \beta_{4k}Pre_AD_{ijt} \times T_i + \beta_{5k}AD_{ijt} \times T_i + \beta_{6k}Post_AD_{ijt} \times T_i + \beta_{7k}TR_{ij} \times T_i + \beta_{8k}T_i + \epsilon_{k,t}.
\end{aligned} \tag{21}$$

and β_k with $k = 1$ ($k = 2$) as a vector of coefficients to be estimated in the input dropping (adding) equation. A significantly positive (negative) coefficient would point to an increase (decrease) in the probability of dropping or adding an input relative to the probability of continued input (non-)use, when changing the value of one of the independent (dummy) variables from 0 to 1, all else assumed unchanged.

As before, T_i is a dummy variable that marks firms that are at a certain point in time using protected inputs, including both importers and non-importers. We include both to account for the possibility that also the decision of non-importers to start using an input might be affected by trade protection. TR_{ij} marks the treated input. Pre_AD_{ijt}, AD_{ijt} and $Post\_AD_{ijt}$ are one respectively in the year before, during and after protection. The model is estimated on the full sample of firm-inputs as well as on a reduced sample of inputs used by firms from the following four sectors: chemicals, plastics and rubber, basic metals and textiles. These are the sectors that most frequently use inputs on which protection is imposed. By running a separate regression on the reduced sample, we intend to account for particularities in these sectors' input dynamics.

Trade protection does not have a significant impact on input dropping (Appendix Table C5). However, firms that use protected inputs tend to increasingly start using other inputs than the protected ones, when protection is imposed (β_5). Firms also tend to add protected inputs less frequently when protection is put in place ($\beta_5 + \beta_2$). The differential effect relative to other inputs is significant (β_2).

5 Empirical Evidence on Output Reallocation

5.1 Identifying Treated Firm-outputs

In this section we consider the within firm reallocation of outputs, induced by antidumping measures on inputs. For this purpose, we need to identify firm-outputs that are made of treated firm-inputs. However, inputs used and products sold are listed separately in our dataset without information on the link between the two, so that a firm level input-output table is not readily available in the data. Nevertheless we establish a link between inputs and outputs and construct a binary input-output correspondence that specifies whether a protected input is used in the production of a particular output or not.

We proceed by first investigating for single-output firms which output is produced with a protected input. Given that single-output firms only sell a single output, it is reasonable to assume that all the inputs that these firms report to use, enter the production of this single output. With this information, we then turn to multi-output firms and one-by-one identify the outputs of these firms that are made of the same input (see Appendix B.3).

Through this procedure, we identify those firms that sell outputs made of protected inputs. For 729 single- and multi-output firms we assign inputs involved in antidumping cases, to corresponding outputs. This is around two thirds of the firms for which such raw material inputs could be identified, resulting in 1200 firm-outputs produced with protected inputs.

5.2 Results on Output Reallocation

We once more revert to triple-differencing in which we compare output reallocation from affected towards unaffected outputs in treated firms with output reallocation in control firms. In analogy to the analysis of input reallocation, we define *treated firms* (*control firms*) as those firms that are importers (non-importers), not affected by protection on the output side and selling outputs made of protected inputs, labelled as *treated outputs in treated firms* (*treated outputs in control firms*). All other outputs sold by these firms are *non-treated outputs in treated firms* (*non-treated outputs in control firms*). These four groups of firm-outputs will enter the regression.

The estimated equation is defined in analogy to equation (20), where output value and quantity now respectively serve as dependent variables, instead of input value and quantity. We then explore whether trade protection on inputs has an impact on the sales of products made of these inputs, considering also investigation and post-treatment effects.

As we identify outputs made of protected inputs only for a subsample of firms, the sample that we end up with is considerably smaller than the one on input reallocation. In addition, the sample of *non-treated outputs* is relatively small for both treated and non-treated firms, given that protected inputs often enter the majority of outputs. This prevents us from running regressions on subsamples, so that we only report results for the full sample of multi-input firms. Despite these limitations, we are able to show the robustness of our results with respect to the estimation methodology by applying both PPML and linear panel (firm-product) fixed effect estimation techniques.

Table 3: Results on output reallocation (control firms: non-importers)

Dependent variable: Sales (firm-output level)

	PPML estimation				Linear FE estimation			
	Value	Quantity	Value	Quantity	Value	Quantity	Value	Quantity
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Pre AD x TR x T (B)			**0.267**	**-1.427*****			**-0.529**	**-0.630***
			(0.511)	**(0.407)**			**(0.344)**	**(0.374)**
Pre AD x T (C)			0.758***	0.790***			0.583**	0.415**
			(0.161)	(0.167)			(0.272)	(0.197)
Pre AD x TR (F)			-0.279	1.435***			0.531*	0.618*
			(0.503)	(0.446)			(0.316)	(0.331)
Pre AD (M)			-0.759***	-0.730***			-0.658**	-0.567***
			(0.170)	(0.144)			(0.254)	(0.169)
AD x TR x T (β)	**-0.201**	**-1.148****	**0.020**	**-1.539*****	**-0.431**	**-0.721***	**-0.495**	**-0.840****
	(0.463)	**(0.447)**	**(0.550)**	**(0.494)**	**(0.588)**	**(0.380)**	**(0.612)**	**(0.421)**
AD x T (γ)	0.930***	1.021**	0.888***	1.168***	0.366	0.817**	0.445	0.895**
	(0.170)	(0.412)	(0.117)	(0.433)	(0.570)	(0.368)	(0.580)	(0.388)
AD x TR (ϕ)	0.112	0.724***	-0.109	1.117***	0.254	0.662*	0.317	0.778**
	(0.412)	(0.157)	(0.504)	(0.296)	(0.562)	(0.338)	(0.583)	(0.376)
AD (μ)	-0.941***	-0.855***	-0.931***	-0.911***	-0.538	-1.089***	-0.686	-1.266***
	(0.184)	(0.197)	(0.136)	(0.247)	(0.548)	(0.362)	(0.558)	(0.389)
Post AD x TR x T (b)	**0.045**	**-0.045**	**0.122**	**-0.373**	**0.260**	**0.100**	**0.218**	**0.024**
	(0.387)	**(0.550)**	**(0.433)**	**(0.569)**	**(0.833)**	**(0.591)**	**(0.843)**	**(0.607)**
Post AD x T (c)	0.661***	0.638	0.716***	0.719	-0.433	-0.030	-0.387	-0.001
	(0.223)	(0.493)	(0.229)	(0.494)	(0.766)	(0.460)	(0.768)	(0.469)
Post AD x TR (f)	0.006	-0.096	-0.076	0.244	-0.280	-0.128	-0.238	-0.055
	(0.279)	(0.242)	(0.330)	(0.290)	(0.752)	(0.458)	(0.759)	(0.474)
Post AD (m)	-0.924***	-0.958**	-1.014***	-0.920***	-0.269	-0.706	-0.397	-0.848*
	(0.223)	(0.392)	(0.237)	(0.330)	(0.723)	(0.468)	(0.722)	(0.476)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm-input FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of firm-inputs	243	238	243	238	243	238	243	238
Number of observations	2929	2840	2929	2840	2728	2653	2728	2653

Notes: ***, ** and * indicate a significance level of 1, 5 and 10%, respectively. Reported standard errors in brackets are cluster robust with clustering at the firm-output level. The table shows results of the regression described by equation (20), estimated with PPML (columns 1-4) and with a linear panel (firm-output) fixed effects estimator (columns 5-8) on the sample of multi-input firms. The regression uses sales value or quantity (at the firm-output level) as dependent variable. *TR* marks treated inputs in both treated and control firms, T identifies all firm-inputs that are used by treated firms, *Pre AD* marks the year before protection is in force, *AD* marks the years of antidumping protection, and *Post AD* marks the years after treatment. Average (pre- & post-)treatment effect on the treated is in bold with β (B & b) as our main coefficient of interest.

Table 3 provides strong evidence for output reallocation effects that work through the imported input channel, confirming Proposition 2 of the theory model. Firms are estimated to reduce sales quantities of outputs, made of protected inputs, by 50-80% vis-à-vis other outputs.[16] While we find strong evidence for a decrease in output quantities due to trade protection, output values

[16] The impact can be calculated as $(\exp(\beta) - 1) * 100$ in %, where β is the estimated coefficient. For example, the estimated coefficient -1.148 in column (2) of Table 3 translates into an impact of -68.2%.

appear to remain unchanged, which is indicative of rising output prices due to trade protection. Indeed, the increase in costs of using the protected input, induced by trade protection, appears to be at least partially passed through to the output price. The next section discusses prices and pass-through in more detail.

6 Empirical Evidence on Prices and Markups

In this section we test proposition 3 of the theory where we show that trade protection on inputs result in a decrease of firm level markups. The mechanism in the theory is that trade protection raises the marginal cost of the outputs that use the protected inputs. This marginal cost increase then raises output prices, but since pass-through is incomplete, we expect markups to go down.

Before we engage in the markup estimation we first look at prices. Based on Table 1 results, we find input prices to be relatively unaffected by the protection. However, input prices in our data do not reflect the "cost of using" an input as they are net of tariffs and also do not include further processing costs in the event that firms switch suppliers and pay the same or a lower price for inputs of lower quality. Also, whenever a firm stops using an input, we no longer observe its price. Unobservable input prices then result in a selection issue that is likely to bias the identification of trade protection on prices if we engaged in triple differencing as in (20).[17] This problem is likely to be serious, given that 14% of non-missing firm-input values and quantities in our data are zero and result in missing price values.

Unobservable prices also arise when assessing the impact of trade protection on output prices through (20) given that there is a substantial amount of product dropping in the data. Nevertheless, when running a triple difference regression as in (20), using output prices of affected outputs as the dependent variable, we find a substantial increase in output prices. We find that firm-output prices on average rise by 80% as a result of trade protection on inputs they are made of. This appears to confirm an increase in the cost of using affected inputs, due to the input trade shock. While the magnitude of the output price rise is within the bounds of the size of typical antidumping tariffs in India (62-90% according to Bown (2012)), its interpretation is not straightforward. In addition to a potential selection bias as discussed above, there are other reasons to be cautious in the interpretation. One is that we established the input-output link at the firm-level through a binary correspondence, which allows us to identify affected outputs e.g. those produced with protected inputs. However, because of its binary nature the input-output correspondence does not give us the intensity in which the affected input is used in a particular output. Ideally, we require information on whether an input is a minor or a major input in the affected output which is lacking. Thus, a high tariff on a minor input may only result in a small increase in the output price, whereas a small tariff on a major input can result in a more substantial output price increase.

[17]This problem does not arise when using input quantities or values as a dependent variable in (20) since whenever they turn zero, a PPML estimator still ensures unbiased coefficients.

Thus, we proceed by estimating firm-level markups in a way that does not rely on firm-input or firm-output price data. The markups results can then be used to infer results on pass-through of costs into output prices. For example, if we find that markups are falling after protection as we do, this implies that marginal cost increases of input-using firms are not fully passed on to output prices but are absorbed in part by the firm.

For estimating markups at the firm level we follow the approach by De Loecker and Warzynski (2012).[18] This approach consists in estimating a production function defined in terms of firm level deflated variables, in order to obtain an output elasticity with respect to a variable factor of production. The ratio of this output elasticity over the share of expenditures on variable factors of production in total sales, results in a firm level markup.

Empirically, this approach consists in estimating a production function in capital, raw materials and labor, and controlling for the unobserved productivity through a control function approach. Similar to De Loecker et al. (2016), we use data on these factors of production from the firm level module of *Prowess* (Companies Accounts data), where expenditures on raw materials are reported as one aggregate number. More formally, we consider a general Cobb-Douglas production function $F(\cdot)$, with variable factors of production X_{jt}^V and capital stock K_{jt} used in the production of output quantity Y_{jt} for firm j in year t. Firm level output also depends on unobserved firm productivity, Θ_{jt}, as follows:

$$Y_{jt} = \Theta_{jt} F(X_{jt}^V, K_{jt}) \tag{22}$$

When estimating the production function from firm level data, physical output Y_{jt} is typically not observed but is proxied for by deflating firm level revenue or sales using industry level price indices. Unobserved price variation at the firm level that differs from the price deflator will enter the error term. This results in a bias when estimating the production function coefficients and output elasticities which needs to be corrected for when using deflated revenue data. To address the simultaneity problem we use a control function approach.[19]

When we consider (22) in logs, the output elasticity of production with respect to a variable factor of production is given by $\Theta_{jt}^{X^V} = \frac{\partial \ln F(\cdot)}{\partial \ln X_{jt}^V}$. Assuming that firms are cost minimizing, it can then be shown that the output elasticity, Θ_{jt}^V, equals the firm level markup, μ_{jt} (defined as the ratio of output price over marginal cost), multiplied by the revenue share of expenditures

[18] A more recent paper by De Loecker, Goldberg, Khandelwal and Pavcnik (2016) decomposes firm-product level output prices into its markup and marginal cost (productivity) component. By measuring markups at the firm-product level, we could be missing a composition effect since the markups of other products made by the firm could also be affected through linkages in supply and/or demand as discussed in section 2.

[19] We follow Levinsohn and Petrin (2003), but instead of electricity consumption, we use fuel consumption to proxy for productivity.

on that particular variable factor of production, $\frac{P^V_{jt} X^V_{jt}}{P_{Y,jt} Y_{jt}}$:[20]

$$\Theta^V_{jt} = \mu_{jt} \frac{P^V_{jt} X^V_{jt}}{P_{Y,jt} Y_{jt}} \tag{23}$$

Thus, in order to obtain a measure of firm level markups, μ_{jt}, we require an estimate of the output elasticity of a variable factor of production and data on the respective expenditure share. The variable factor of production we consider for this purpose is firm level raw materials. The revenue share on expenditures on a factor of production can directly be observed from the data but to obtain the output elasticity, Θ^V_{jt}, we need to estimate the production function in a consistent way. Estimations are performed separately by sector where the estimated output elasticities are the same for all firms within a sector, but varies across firms by the share of raw materials in firm revenue. Appendix Table D1 lists average output elasticities of labor, materials and capital for sectors with sufficient observations and Table D2 reports average estimated markups by sector.

When considering the affected firms and their markup distribution before and after protection, we see that the kernel density function after protection has shifted to the left, as shown in Figure D1. Based on Figure D1, we already see that the average markup after protection is lower than before protection for those firms that are using inputs subject to the trade shock.

Table 4: Results on firm level markups

Dependent variable: Firm-level markups (ln)

	Control firms: Non-importers		Control firms: Matched	
	(1)	(2)	(3)	(4)
AD x T (β)	**-0.111*****	**-0.368*****	**-0.217*****	**-0.277*****
	(0.064)	**(0.093)**	**(0.074)**	**(0.085)**
Post AD x T (b)		**-0.792*****		**-0.441****
		(0.201)		**(0.252)**
Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Number of observations	928	928	1115	1115

Notes: ***, ** and * indicate a significance level of 1, 5 and 10%, respectively. Reported standard errors in brackets are cluster robust with clustering at the firm level. Average (post-)treatment effect on the treated is in bold with β (b) as our main coefficient of interest. Reported results are based on a double-difference regression. T is a dummy variable that marks treated firms. AD is a dummy variable that marks the period of protection. *Post AD* is a dummy variable defined as in equation (20), marking the years after protection has expired. The dependent variable of firm level markups was estimated using the De Loecker and Warzynski (2012) method.

Next, we more formally test our proposition 3 arising from the theory, that input reallocation results in a reduction in markups. For this purpose we use a simple double-difference specifica-

[20] Empirically the numerator of that ratio is estimated on a fitted regression line, requiring a further correction in the denominator where the nominal share of expenditures on factors of production in actual sales needs to be weighted by (exponent of) the residuals from the production function (estimated in logs).

tion, with matched firms in our control group. We report results in Table 4 under De Loecker and Warzynski (2012) with and without post-protection effects.

Regardless of the estimated specification, we note that markups significantly drop after a trade shock hits input-using firms. Markups fall both during the protection period and continue to fall after the five-year protection period. These results confirm proposition 3 derived in the theory and are consistent with incomplete pass-through from antidumping tariffs into prices. The reduction in markups, reflect that antidumping tariffs are not fully passed on to Indian consumers but partly absorbed by input-using firms which puts downward pressure on firm level markups.

7 Conclusion

This paper adds to the literature on trade policy and how that affects multi-product firms. It provides firm-product level evidence on the impact of import protection, imposed on raw material inputs, on the input and output choices of those firms that use these inputs in their production process. We match a unique Indian firm-product level dataset on raw material input consumption with information on Indian trade policy in the form of antidumping duties, and find strong evidence that Indian importers engage in input reallocation in response to trade protection. Using triple-difference regressions with alternative control groups, our findings show that importing firms reduce the use of the protected input by 25-40%, relative to other inputs. This reduction occurs both in terms of values and quantities and is mostly driven by an adjustment along the intensive margin with input dropping playing only a minor role. Results are robust to the use of alternative estimation methodologies and specifications, and hold in various subsamples. Moreover, our results are not driven by any particular sector.

We also find that multi-output firms reduce their consumption of the protected input by more than single-output firms. A potential explanation for this is that multi-output firms can more easily channel resources into other existing product lines. We also find evidence of an "investigation effect" e.g. where input reallocation already takes place in the investigation period prior to the first year antidumping protection. This result indicates that some input users adjust their input use already in anticipation of an antidumping measure. Finally, even though antidumping measures are temporary measures of trade protection, results suggest that their impact is rather permanent, so that firms do not fully switch back to their initial input mix, once protection expires.

Besides input reallocation, we also find evidence of output reallocation. Based on a binary firm level input-output correspondence, we match protected inputs to outputs at the firm level. Resulting from that we find that firms strongly reduce sales of products that are made of protected inputs, relative to other products in response to trade protection. Thus, our results show that trade policy can cause sizeable distortions in importing firms' input use and production patterns. Moreover, we show that changes in firms' input mix go hand in hand with changes in the output mix, suggesting that trade protection on inputs has an effect on firms' output choices. We find that prices of outputs made of the protected inputs are rising, while the quantity sold of these outputs is going down. But despite rising output prices, we find markups of input-using firms to decrease. Our results therefore document negative aspects of trade protection hitherto unaccounted for.

Especially in a world where production gets more fragmented across borders, input and output reallocation effects may play an increasingly important role for a large number of firms of the input-using industry. This paper has shown that trade protection can have adverse effects on firms in domestic downstream industries that use protected products as inputs and whose interests are less likely to be considered. Traditional trade policy measures still operate under the maintained assumption that trade protection benefits domestic firms. While this may have been true in an era where the traditional vision on a firm was that it produced and sourced domestically, this paper shows that this no longer holds in a world where many firms source internationally.

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Appendix — *For Online Publication* —

A Theoretical Model

To show input reallocation, we start by defining the quantity share of foreign inputs in total inputs for a firm-variety that sources the foreign input from abroad both before and after the protection (a variety of type m). In the text, we already showed that the price increase of the sourced foreign input will result in input substitutability where the variety will be produced with a lower amount of the protected input and more of the domestic input (channel 1) and a quantity effect (channel 2) where the price increase of the foreign input results in an increase in the output price and lowers the demand for both inputs used in the firm-variety of type m.

Proof of Proposition 1

In the following, $\mathcal{M}$, $\mathcal{W}$ and $\mathcal{N}$ will denote subsets of product market $\mathcal{S}$, referring respectively to the set of all type m varieties, the set of type w varieties (a subset of type m varieties that switch after trade protection to type n) and the set of type n varieties. To show input reallocation, we define the quantity share of affected foreign material inputs in total inputs within the multi-product firm with type m and type n varieties as follows:

$$S_{input} = \frac{\sum\limits_{s\in\mathcal{M}} x_{1I}}{\sum\limits_{s\in\mathcal{M}} x_{1I} + \sum\limits_{s\in\mathcal{M}} x_2 + \sum\limits_{s\in\mathcal{N}} x_{1D} + \sum\limits_{s\in\mathcal{N}} x_2} \tag{A1}$$

We now use a property of ratios to show that S_{input} goes down after trade protection. The ratio S_{input} goes down whenever the proportionate drop in $\sum\limits_{s\in\mathcal{M}} x_{1I}$ is larger than the proportionate drop in $(\sum\limits_{s\in\mathcal{M}} x_2 + \sum\limits_{s\in\mathcal{N}} x_{1D} + \sum\limits_{s\in\mathcal{N}} x_2)$ (when this last term rises, S_{input} always drops).

Put differently, we need to verify whether the following condition holds:

$$\frac{\partial S_{input}}{\partial p_{x_{1I}}} \Leftrightarrow \frac{\sum\limits_{s\in(\mathcal{M}\setminus\mathcal{W})} x'_{1I} - \sum\limits_{s\in\mathcal{M}} x_{1I}}{\sum\limits_{s\in\mathcal{M}} x_{1I}} < \frac{\sum\limits_{s\in(\mathcal{M}\setminus\mathcal{W})} x'_2 + \sum\limits_{s\in(\mathcal{N}\cup\mathcal{W})} x_{1D} + \sum\limits_{s\in(\mathcal{N}\cup\mathcal{W})} x_2 - \sum\limits_{s\in\mathcal{M}} x_2 - \sum\limits_{s\in\mathcal{N}} x_{1D} - \sum\limits_{s\in\mathcal{N}} x_2}{\sum\limits_{s\in\mathcal{M}} x_2 + \sum\limits_{s\in\mathcal{N}} x_{1D} + \sum\limits_{s\in\mathcal{N}} x_2} \tag{A2}$$

where x'_{1I} and x'_2 are the new demands for foreign input 1 and 2 (after trade protection on foreign input 1) in type m varieties. We indicate "switching varieties" by w, e.g. these are the varieties that before trade protection are type m, but after trade protection source input 1 domestically similar to type n varieties.

For an infinitesimal number of switchers ($w \to 0$), we can simplify the right-hand side in (A2). It can also be noted that type n varieties do not have a change in demand of inputs under trade protection which simplifies (A2) even further. Thus, S_{input} drops if (A3) holds:[21]

$$\frac{\sum\limits_{s\in\mathcal{M}} x'_{1I} - \sum\limits_{s\in\mathcal{M}} x_{1I}}{\sum\limits_{s\in\mathcal{M}} x_{1I}} < \frac{\sum\limits_{s\in\mathcal{M}} x'_{2} - \sum\limits_{s\in\mathcal{M}} x_{2}}{\sum\limits_{s\in\mathcal{M}} x_{2} + \sum\limits_{s\in\mathcal{N}} x_{1D} + \sum\limits_{s\in\mathcal{N}} x_{2}} \tag{A3}$$

A sufficient condition for (A3) to hold is given by (A4) below:[22]

$$\frac{\sum\limits_{s\in\mathcal{M}} x'_{1I} - \sum\limits_{s\in\mathcal{M}} x_{1I}}{\sum\limits_{s\in\mathcal{M}} x_{1I}} < \frac{\sum\limits_{s\in\mathcal{M}} x'_{2} - \sum\limits_{s\in\mathcal{M}} x_{2}}{\sum\limits_{s\in\mathcal{M}} x_{2}} \tag{A4}$$

In words, (A4) states that the quantity share of affected inputs in total input expenditures will decrease if the proportional drop in the demand for the foreign input 1 in all type m varieties is larger than the proportional drop in the demand for the domestic input 2 in all type m varieties.

We know that expression (A4) holds, as we have shown this to hold for every type m variety individually.

Per variety of type m, we now inspect the quantity share of foreign input 1 in total input use

$$S^{(m)} = \frac{x_{1I}}{x_{1I} + x_2} \tag{A5}$$

In (A6), we show that the demand for foreign input 1 (in the numerator of (A5)) unambiguously falls with trade protection, where (A6) is the joint effect of an input substitutability and a quantity effect:

$$\frac{\partial x_{1I}}{\partial p_{x_{1I}}} = \frac{-(x_{1I})^2}{p_M \cdot M}\left[\frac{p_M \cdot M}{2\beta q(s)^2} + a + \theta \cdot \left(\left(\frac{p_M}{p_{x_{1I}}}\right)^{1-\theta} - 1\right)\right] < 0 \tag{A6}$$

But for the input demand for the domestic input 2 (in the denominator of (A5)), the input substitutability (a positive effect of channel 1) and the quantity effect (a negative effect of channel 2) work in opposite directions, resulting in an ambiguous effect from trade protection as shown in (A7):

$$\frac{\partial x_2}{\partial p_{x_{1I}}} = -\frac{x_{1I} \cdot x_2}{p_M \cdot M}\left(\frac{p_M M}{2\beta q(s)^2} + a - \theta\right) \gtreqless 0 \tag{A7}$$

Thus, from (A6), we know that x_{1I} unambiguously falls, but from (A7) we know that x_2 may rise or fall. Thus, we need to consider what happens to the ratio in (A5) under both scenarios for x_2.

[21] The exact number of switching varieties within the multi-output firm, w, cannot be derived from the model, as this will depend on the size difference between the fixed cost of sourcing internationally, $F_{x_{1I}}$, and the fixed cost of sourcing input 1 domestically, $F_{x_{1D}}$, which we did not specify. Thus we want a result on the number of switchers that is as general as possible and holds even for a very small number of them.

[22] More generally, it suffices to show $\frac{A}{B} > \frac{A'}{B'}$ in order for $\frac{A}{B} > \frac{A'}{B'+C}$, provided $C > 0$ e.g. adding a positive number in the denominator will always make the ratio smaller e.g. $\frac{A}{B} > \frac{A'}{B'} > \frac{A'}{B'+C}$. But note that the change in demands in (A2) are negative (a drop) so the inequality signs are reversed.

When x_2 rises or remains constant, input reallocation will always occur, e.g. $\frac{\partial S^{(m)}}{\partial p_{1I}} < 0$ as ratio S_{input} always falls when x_{1I} falls and x_2 rises in type m varieties.

When x_2 falls, the ratio in (A5) still falls as long as the proportionate drop in x_2 is smaller than the proportionate drop in x_{1I}. Put differently, the ratio $S^{(m)}$ falls as long as the proportionate drop in x_{1I} is larger than the proportionate drop in x_2. This condition is satisfied, which can be seen below in (A8) and which is arrived at by comparing the proportionate drop in in x_{1I} (absolute levels) to that in x_2:

$$\left| \frac{\frac{\partial x_{1I}}{\partial p_{x_{1I}}}}{x_{1I}} \right| = \frac{\frac{\partial x_2}{\partial p_{x_{1I}}}}{x_2} + \theta \cdot \left(\frac{p_M}{p_{x_{1I}}} \right)^{1-\theta} \tag{A8}$$

Given (A8), we have shown input reallocation always to occur within a type m variety and subsequently we have also shown condition (A4) to hold, which sums over all type m varieties such that $\frac{\partial S_{input}}{\partial p_{x_{1I}}} < 0$.

Proof of Proposition 2

Next, we show output reallocation to result from trade protection on foreign input 1 making input 1 more expensive. This is relatively easy to show, given that the number of type m varieties within the multi-output firm after protection will go down e.g. some varieties will quit sourcing input 1 from abroad and start sourcing it domestically. Thus, the share of type m varieties produced in total output produced by the multi-output firm will go down. To see this consider the following ratio in which we express the quantity share of affected output in total firm output:

$$S_{output} = \frac{\sum\limits_{i \in \mathcal{M}} q_{ji}(m)}{\sum\limits_{i \in \mathcal{M}} q_{ji}(m) + \sum\limits_{i \in \mathcal{N}} q_{ji}(n)} \tag{A9}$$

To prove that S_{output} falls we rely on a property of ratios that we have also used before e.g. the ratio in (A9) will fall when there is a drop in the numerator, $\sum\limits_{i \in \mathcal{M}} q_{ji}(m)$ together with a rise or "no change" in the second term of the denominator, $\sum\limits_{i \in \mathcal{N}} q_{ji}(n)$. It is now straightforward to show that this is the case with trade protection.[23]

Taking the derivative of $q_{ji}(m)$ with respect to the price of input 1 for each variety $i \in \mathcal{M}$, we get a decrease after protection, as shown by (A10):

$$\frac{\partial q(s)}{\partial p_{x_{1I}}} = \frac{-x_{1I}}{2\beta q(s)} < 0 \tag{A10}$$

Moreover, the number of type m varieties falls after trade protection as some type m varieties switch and become n-type. Together this ensures that the numerator in (A9) falls after protection.

[23]More generally, ratio $\frac{A}{A+B}$ falls whenever A falls and B rises or remains constant in absolute levels.

For the second term in the denominator, we know that after protection, for new n-type varieties, $q_{ji}(n)$, will be positive or (in an extreme case of an infinitesimal small number of switching varieties) zero. Moreover there will be no change in $q_{ji}(n)$, for the old n-type varieties (as these are not affected by trade policy). Combined e.g. the output change for the switchers and the old n-type varieties, this implies that $\sum_{i \in \mathcal{N}} q_{ji}(n)$ rises or remains unchanged.

Together this results in output reallocation, reducing the share in (A9) e.g. for every firm j, S^j_{output} goes down after protection, e.g. $\frac{\partial S_{output}}{\partial p_{x_{1I}}} < 0$.

Proof of Proposition 3

Equation (3) in the main text for unit cost can be written as follows, when substituting $a+b=1$ and $p_L = 1$:

$$\tag{A11}$$

$$\begin{aligned} c(s) &= \frac{1}{A(s)} \left[\left(\frac{a p_M}{b} \right)^b + p_M^{1-a} \left(\frac{b}{a} \right)^a \right] \qquad \text{(A12)} \\ &= \frac{1}{A(s)} \frac{p_M^b}{b} \left(\frac{b}{a} \right)^a \end{aligned}$$

For a type m variety, we see that trade protection leads to an increase in unit cost:

$$\begin{aligned} \frac{\partial c(s)}{\partial p_{x_{1I}}} &= \frac{1}{A(s)} \left(\frac{b}{a} \right)^a p_M^{b-1} \cdot \frac{\partial p_M}{\partial p_{x_{1I}}} \\ &= \frac{b c(s)}{p_M} \left(\frac{p_M}{p_{x_{1I}}} \right)^\theta > 0 \end{aligned} \tag{A13}$$

The markup is $\frac{c_D - c(s)}{2}$. Therefore it holds that

$$\frac{\partial \mu(s)}{\partial p_{x_{1I}}} = -\frac{1}{2} \frac{\partial c(s)}{\partial p_{x_{1I}}} = -\frac{1}{2} \frac{b c(s)}{p_M} \left(\frac{p_M}{p_{x_{1I}}} \right)^\theta < 0 \tag{A14}$$

so markups decrease after trade protection for type m varieties.

For a type n variety, there is no change in markups after protection, since

$$\frac{\partial \mu(n)}{\partial p_{x_{1I}}} = -\frac{1}{2} \frac{\partial c(n)}{\partial p_{x_{1I}}} = 0 \tag{A15}$$

given that the unit cost of an n-type is not affected by trade protection.

A switcher w was an m-type before protection and becomes an n-type after protection. The effect on its markup is given by

$$\mu(n) - \mu(m) = \frac{c(m) - c(n)}{2} < 0 \tag{A16}$$

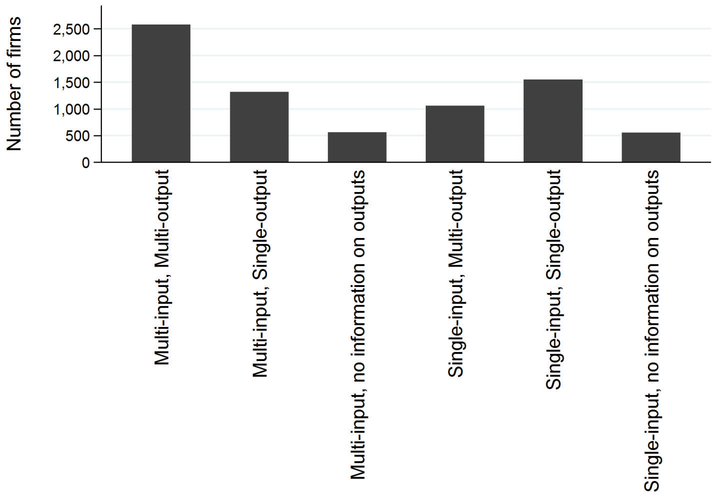
so that the markup decreases for a switching variety w. This is because the variable costs for n-type varieties is higher than for m-type varieties, $c(m) < c(n)$, due to $p_{x_{1I}} < p_{x_{1D}}$.

To summarize, while markups for type n varieties are unaffected by trade protection, markups for type m varieties go down. Also for varieties w that switch, markups decrease as the variable cost in production goes up and pass-through in linear demand is incomplete. For the firm as a whole, the model thus predicts a decrease in markups, independent of the number of each type of varieties.

B Data

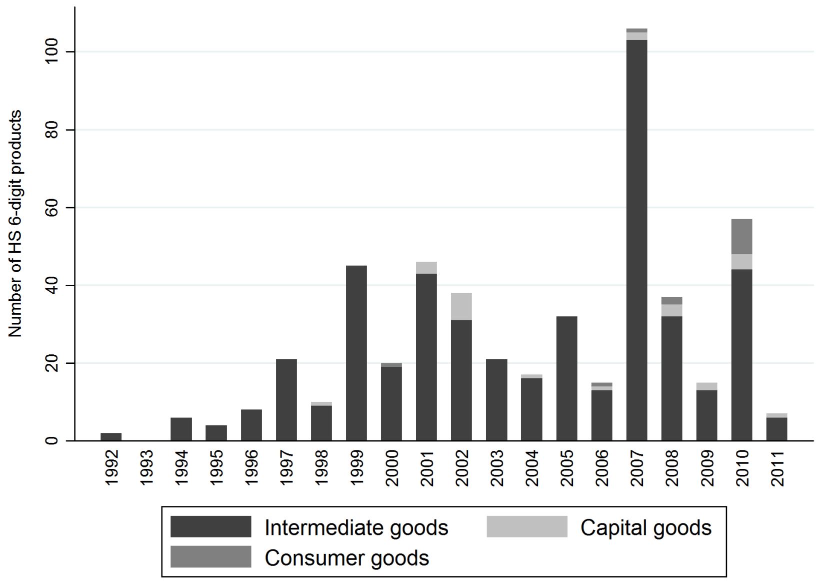
B.1 Descriptive Statistics

Figure B1: Number of firms in the Indian firm-input data, by type



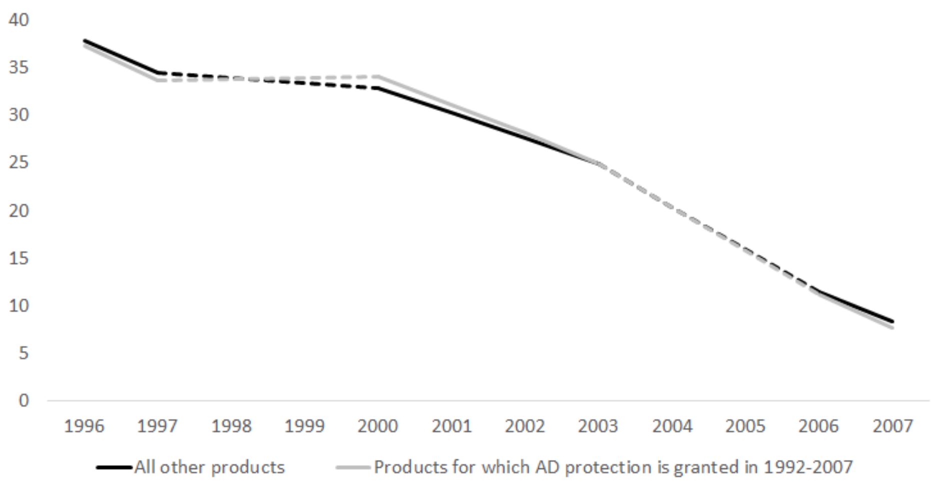
Source: Authors' calculations based on the *Prowess* database.

Figure B2: Number of products (HS 6-digit) in affirmative antidumping cases, by type



Source: Authors' calculations based on Bown (2012), Indian national sources and BEC classification.
Notes: Only those products are included for which there is an unambiguous concordance between different HS revisions.

Figure B3: Average applied MFN tariffs by type of product in selected sectors, 1996-2007 (in %)



Source: Authors' calculations based on Bown (2012) and WTO's *Integrates Database* (IDB).
Notes: The figure shows the Indian average applied MFN tariff for products in the chemicals, rubber and plastics, textiles, machinery and base metals sector (simple average). Products are defined at the HS-1996 level; the sample of products for which AD protection is granted at least once in 1992-2007 consists of 376 products and the sample of all other products consists of 2,018 products. To ensure consistency over time, only those products are included for which there is an unambiguous concordance between different HS revisions. The dashed line connects data points in years for which no tariff data are available.

Table B1: Number of affirmative antidumping cases by sector, 1992-2011

	Number of cases	% of cases
Food, beverages (HS section IV)	3	0.6
Mineral products (V)	5	1.0
Chemicals (VI)	220	44.8
Rubber, plastics (VII)	81	16.5
Wood (IX)	4	0.8
Pulp and paper (X)	7	1.4
Textiles (XI)	57	11.6
Footwear (XII)	1	0.2
Stones, glass (XIII)	8	1.6
Base metals (XV)	45	9.2
Machinery (XVI)	55	11.2
Transport (XVII)	2	0.4
Instruments (XVIII)	3	0.6
Total	*491*	*100*

Source: Authors' calculations based on Bown (2012).
Notes: Antidumping cases are counted separately for each country targeted in the antidumping case. After each sector, the corresponding HS section is noted in brackets. An antidumping case is assigned to a sector on the basis of the products that are involved.

B.2 Identification of Protected Firm-inputs

This section of the Data Appendix describes how product-level data on antidumping cases from the *Global Antidumping Database* are matched with firm-input-level data from the *Prowess* database. The objective is to identify input-using firms and firm-inputs involved in antidumping cases. The main challenge is firms reporting firm-input data do not use any product classification only product names, in line with the regulations provided in the *1956 Companies Act* that obliges firms to disclose product-level information. To overcome this limitation, we develop a procedure that matches the product names mentioned in Indian antidumping cases with raw material input names reported in the firm-input data module of the *Prowess* database.

In order to illustrate this matching procedure, we use the example of *Caustic Soda*. *Caustic Soda* is a product that occurs in five antidumping cases between 2000 and 2010. The objective of the matching procedure is to identify *Caustic Soda* amongst the raw material inputs reported in the firm-product data module of *Prowess*. The matching procedure consists of two steps.

Step 1: Selection of key words
We identify key words and word fragments that we require to match the product names reported in the firm-input data module of *Prowess* to contain, either individually or in combination. These words and word fragments are carefully chosen on the basis of the product names that are originally mentioned in the Indian antidumping cases. We also look up synonyms of these product names. This search is conducted through internet search engines and every synonym

that we found was verified through various sources. We use word fragments instead of full words whenever this is likely to help capturing product names written with spelling mistakes or in a different form.

For example, for *Caustic Soda*, *Caustic Lye* and *Sodium Hydroxide* were identified as synonyms. On the basis of these product names, four key word fragments were chosen, which are *Caust*, *Sod*, *Hydroxid* and *Lye*. The word fragment *Caust* picks up any product name that contains the words *Caustic* and *Caustics*. *Sod* takes into account *Soda* as well as *Sodium* and *Hydroxid* identifies product names containing the correctly spelled word *Hydroxide* as well as *Hydroxid.* After checking that alternative spellings of *Lye* cannot be identified in the firm-product data, we leave *Lye* unchanged.

Step 2: Determination of the matching rule
We define a matching rule which imposes that only inputs that contain certain combinations of key words and word fragments are matched to antidumping cases. For the case of *Caustic Soda*, the matching rule can be written as follows: (*Caust* AND *Sod*) OR (*Sod* AND *Hydroxid*) OR ((*Caust* OR *Sod*) AND *Lye*). In words, only inputs are picked up that contain either both *Caust* and *Sod*, or both *Sod* and *Hydroxid*, or *Lye* combined with *Caust* or *Sod.* This way we avoid including inputs such as *Mineral Water Soda*, *Sodium Metal* or *Sodium Bio Sulphate* which would not correspond to anything close to *Caustic Soda* and result in incorrect matches.

Results of matching procedure
We identify 1133 firms that report the use of raw material inputs that are involved in an antidumping case at least once between 1992 and 2007, corresponding to 1436 firm raw material input observations. This is 14.9% of all firms in the dataset and 7.3% of all firm-inputs. On the whole, we find for 73.0% of all antidumping cases initiated in India between 1992 and 2007 at least one corresponding raw material input in the firm-product data.

Table B2: Results of matching procedure for *Caustic Soda*

Product names identified in firm-input data		
Caustic Soda	Caustic Soda Lye/Flakes	Caustic Soda Lye
Caustic Soda Flakes	Caustic Soda Lye/Flacks	Caustic Soda Solution
Caustic Lye	Caustic Soda Flaks	Caustic Soda/Potash
Soda Ash, Caustic Soda	Sodium/Potassium Hydroxide	Soda Caustic
Sodium Hydroxide Solution	Caustic Soda Lye & Flakes	Caustics Soda Lye/Flakes
Caustic Soda	Caustic Soda/Lye	Caustic Soda Lye (48.5%)
Cuastic Soda Lye	Caustic Lye/Flakes	Sodium Hydroxide
Chemicals Like Caustic Soda, Sodium Silicate Etc.		

Table B2 illustrates the matching procedure. It matches 22 names of raw material inputs in the firm-input module of the *Prowess* database to *Caustic Soda.* For antidumping cases on other products the procedure works similarly.[24]

[24]Key words and word fragments, matching rules and matching results for all other products involved in

B.3 Identification of Firm-outputs Produced with Protected Firm-inputs

This section of the Data Appendix desribes the procedure that is used to identify outputs that are produced with raw material inputs involved in antidumping cases. In the data, we have both information on firms' use of different raw material inputs and firms' sales of outputs. However, there is no firm-level input-output table available link the two. To remedy, we develop our own input-output correspondence which we describe below in detail.

Step 1: Input-output correspondence for single-output firms
In a first step, we restrict the sample of firm-output observations to single-output firms for which we identify at least one input involved in an antidumping case. There are 315 single-output firms involved in antidumping cases through at least one of the inputs that are used. These 315 firms cover 54.5% of all antidumping cases initiated between 1992 and 2007 and 74.7% of the antidumping cases to which the matching procedure described in Appendix 2.1 could match at least one raw material input in the firm-product data. Given that these firms sell only one product, it is reasonable to assume that any consumed raw material input enters the production of this product. On the basis of this assumption, we obtain a list of 377 inputs that are unambiguously assigned to an output.

Step 2: Input-output correspondence for multi-output firms
The list of 377 input-output pairs obtained from single-output firms can, give an indication of the outputs for which inputs involved in these cases are used. There are 648 multi-output firms which use one of these inputs and report to sell 3406 products. Based on the information from single-output firms as well as on common knowledge and internet-based search, we then assign 1058 out of the 3406 products to inputs involved in antidumping cases. For 443 of the 648 multi-output firms, we identify at least one output for which inputs involved in antidumping cases are used.

Some inputs of multi-output firms are not assigned to any output. This is either because we cannot identify the outputs that are produced with the input or the corresponding antidumping case is not covered by the input-output pairs obtained from single-output firms. For 29 of the 443 multi-output firms for which we identify an input-output correspondence also use inputs for which such a link cannot be established. For the analysis in section 5, these 29 firms are dropped, so that we end up with a sample of 885 firm-product observations for sales belonging to 414 multi-output firms.

Results of matching procedure
For 729 (single- and multi-output) firms we are able to assign all those inputs that are involved in antidumping cases to corresponding outputs. These are 64.3% of the 1133 firms for which such raw material inputs could be identified. 1200 outputs are marked as being produced with such inputs.

antidumping cases are available upon request from the authors.

C Additional Results on Input Reallocation

Table C1: Additional results on input reallocation, single- and multi-output firms (control firms: matched)

Dependent variable: Raw material input use (firm-input level)

	Single-Output Firms		Multi-Output Firms	
	Value	Quantity	Value	Quantity
	(1)	(2)	(3)	(4)
AD x TR x T (β)	**-0.272**	**0.129**	**-0.390****	**-0.630**
	(0.233)	**(0.194)**	**(0.157)**	**(0.404)**
AD x T (γ)	0.060	-0.062	0.108	0.023
	(0.206)	(0.120)	(0.092)	(0.110)
AD x TR (ϕ)	-0.100	-0.053	0.080	0.616*
	(0.114)	(0.161)	(0.115)	(0.332)
AD (μ)	0.052	-0.159	-0.108	-0.102
	(0.080)	(0.178)	(0.068)	(0.070)
Post AD x TR x T (b)	**0.383**	**-0.584*****	**-0.594****	**-0.696***
	(0.320)	**(0.189)**	**(0.300)**	**(0.405)**
Post AD x T (c)	-0.959***	-0.485***	0.383*	0.095
	(0.233)	(0.110)	(0.212)	(0.165)
Post AD x TR (f)	-0.563***	0.671***	0.133	0.617**
	(0.196)	(0.134)	(0.183)	(0.298)
Post AD (m)	0.278*	-0.455	-0.507***	-0.225**
	(0.165)	(0.292)	(0.180)	(0.108)
Year FE	Yes	Yes	Yes	Yes
Firm-input FE	Yes	Yes	Yes	Yes
Number of firm-inputs	397	390	906	874
Number of observations	3327	3257	7913	7669

Notes: See Table 1.

Table C2: Additional results on input reallocation, by firm size (control firms: non-importers)

Dependent variable: Raw material input use (firm-input level)				
	Small firms		Large firms	
	Value	Quantity	Value	Quantity
	(1)	(2)	(3)	(4)
Pre AD x TR x T (B)	**-0.304**	**0.227**	**-0.734****	**-1.559****
	(0.351)	**(0.256)**	**(0.364)**	**(0.636)**
Pre AD x T (C)	-0.022	0.095	0.490*	1.547**
	(0.283)	(0.110)	(0.284)	(0.653)
Pre AD x TR (F)	0.500*	-0.003	0.465**	1.124**
	(0.259)	(0.154)	(0.219)	(0.534)
Pre AD (M)	-0.433**	-0.109	-0.290	-1.213**
	(0.179)	(0.087)	(0.182)	(0.616)
AD x TR x T (β)	**-0.247**	**-0.198**	**-0.920****	**-0.944****
	(0.527)	**(0.391)**	**(0.367)**	**(0.439)**
AD x T (γ)	-0.171	0.500***	0.616**	1.567***
	(0.333)	(0.180)	(0.256)	(0.446)
AD x TR (ϕ)	0.445	0.252	0.379	0.536
	(0.523)	(0.322)	(0.240)	(0.386)
AD (μ)	-0.548	-0.323*	-0.316	-1.445***
	(0.460)	(0.189)	(0.206)	(0.487)
Post AD x TR x T (b)	**-1.867*****	**-1.890*****	**-0.913****	**0.406**
	(0.698)	**(0.451)**	**(0.432)**	**(0.619)**
Post AD x T (c)	1.281***	0.297	0.714***	0.288
	(0.393)	(0.315)	(0.234)	(0.540)
Post AD x TR (f)	1.516**	0.997***	0.289	0.203
	(0.620)	(0.302)	(0.307)	(0.403)
Post AD (m)	-1.526***	0.279	-0.502***	-1.416***
	(0.572)	(0.221)	(0.155)	(0.528)
Year FE	Yes	Yes	Yes	Yes
Firm-input FE	Yes	Yes	Yes	Yes
Number of firm-inputs	348	340	309	302
Number of observations	2675	2612	2772	2718

Notes: See Table 1.

Table C3: Additional results on input reallocation, by share of input value under protection (control firms: non-importers)

	Dependent variable: Raw material input use (firm-input level)			
	Small share (< 20%)		Large share (> 20%)	
	Value	Quantity	Value	Quantity
	(1)	(2)	(3)	(4)
Pre AD x TR x T (B)	**-0.272**	**-0.519**	**-0.573*****	**-1.741*****
	(0.391)	**(0.392)**	**(0.208)**	**(0.424)**
Pre AD x T (C)	0.524	0.271	0.289*	2.053***
	(0.323)	(0.206)	(0.159)	(0.424)
Pre AD x TR (F)	0.073	0.270	0.417**	1.385***
	(0.170)	(0.316)	(0.189)	(0.378)
Pre AD (M)	-0.429**	-0.213	0.039	-1.544***
	(0.215)	(0.189)	(0.137)	(0.388)
AD x TR x T (β)	**-0.066**	**-1.468*****	**-0.748*****	**-1.099****
	(0.454)	**(0.539)**	**(0.248)**	**(0.488)**
AD x T (γ)	0.692**	0.820***	0.323**	1.980***
	(0.292)	(0.085)	(0.152)	(0.452)
AD x TR (ϕ)	-0.091	0.774	0.362	0.811**
	(0.208)	(0.489)	(0.221)	(0.391)
AD (μ)	-0.479**	-0.790***	0.091	-1.586***
	(0.236)	(0.288)	(0.148)	(0.445)
Post AD x TR x T (b)	**-0.517**	**-1.744*****	**-1.062*****	**-0.542**
	(0.931)	**(0.524)**	**(0.346)**	**(0.432)**
Post AD x T (c)	0.817***	-0.451	0.732***	1.476***
	(0.299)	(0.386)	(0.183)	(0.358)
Post AD x TR (f)	-0.210	1.445***	0.527**	0.429
	(0.825)	(0.338)	(0.263)	(0.265)
Post AD (m)	-0.775***	-0.702*	-0.188	-1.367***
	(0.203)	(0.393)	(0.161)	(0.440)
Year FE	Yes	Yes	Yes	Yes
Firm-input FE	Yes	Yes	Yes	Yes
Number of firm-inputs	358	339	255	248
Number of observations	3108	2982	2059	1978

Notes: See Table 1.

Table C4: Additional results on input reallocation, by sector (control firms: matched)

	Dependent variable: Raw material input use (firm-input level)					
	Chemicals, Value	Chemicals, Quantity	Non-Chemicals, Value	Non-Chemicals, Quantity	Non-Plastics, Value	Non-Plastics, Quantity
	(1)	(2)	(3)	(4)	(5)	(6)
AD x TR x T (β)	**-0.375***	**-0.723**	**-0.306****	**-0.105**	**-0.358****	**-0.561**
	(0.222)	**(0.692)**	**(0.142)**	**(0.156)**	**(0.150)**	**(0.396)**
AD x T (γ)	0.110	-0.325	0.032	0.086	0.136	0.024
	(0.148)	(0.457)	(0.068)	(0.098)	(0.093)	(0.091)
AD x TR (ϕ)	0.066	0.837*	0.067	0.074	0.029	0.586*
	(0.173)	(0.437)	(0.083)	(0.121)	(0.110)	(0.350)
AD (μ)	-0.089	-0.941**	-0.071	-0.045	-0.120**	-0.229
	(0.131)	(0.394)	(0.049)	(0.064)	(0.060)	(0.167)
Post AD x TR x T (b)	**-0.403**	**0.034**	**-0.435**	**-1.119*****	**-0.455**	**-0.838****
	(0.391)	**(0.522)**	**(0.319)**	**(0.256)**	**(0.306)**	**(0.411)**
Post AD x T (c)	0.206	-0.693*	0.099	0.313*	0.257	0.043
	(0.328)	(0.394)	(0.220)	(0.180)	(0.234)	(0.172)
Post AD x TR (f)	-0.068	0.189	0.087	0.691***	-0.027	0.709**
	(0.279)	(0.284)	(0.188)	(0.134)	(0.203)	(0.311)
Post AD (m)	-0.190	-0.870***	-0.280*	-0.240***	-0.349*	-0.251**
	(0.285)	(0.283)	(0.152)	(0.078)	(0.200)	(0.125)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm-input FE	Yes	Yes	Yes	Yes	Yes	Yes
Number of firm-inputs	557	538	746	726	1153	1117
Number of observations	4603	4456	6637	6470	9877	9567

	Non-Metals, Value	Non-Metals, Quantity	Non-Textiles, Value	Non-Textiles, Quantity	Only Chemicals Plastics Metals Textiles, Value	Only Chemicals Plastics Metals Textiles, Quantity
	(7)	(8)	(9)	(10)	(11)	(12)
AD x TR x T (β)	**-0.267**	**-0.652***	**-0.333****	**-0.581**	**-0.393*****	**-0.605**
	(0.174)	**(0.376)**	**(0.136)**	**(0.394)**	**(0.148)**	**(0.386)**
AD x T (γ)	0.003	0.127	0.075	-0.024	0.129	0.004
	(0.128)	(0.088)	(0.082)	(0.086)	(0.096)	(0.088)
AD x TR (ϕ)	0.017	0.542*	0.025	0.599*	0.054	0.519
	(0.097)	(0.329)	(0.093)	(0.350)	(0.118)	(0.336)
AD (μ)	-0.073	-0.199**	-0.070	-0.197**	-0.128	-0.137
	(0.057)	(0.092)	(0.054)	(0.096)	(0.087)	(0.085)
Post AD x TR x T (b)	**-0.384**	**-0.836****	**-0.429**	**-0.573**	**-0.438**	**-0.537**
	(0.327)	**(0.386)**	**(0.307)**	**(0.371)**	**(0.330)**	**(0.438)**
Post AD x T (c)	0.197	0.067	0.270	-0.044	0.221	-0.215
	(0.248)	(0.156)	(0.235)	(0.162)	(0.259)	(0.137)
Post AD x TR (f)	-0.035	0.682**	-0.051	0.497*	-0.026	0.631*
	(0.206)	(0.296)	(0.206)	(0.277)	(0.240)	(0.365)
Post AD (m)	-0.360*	-0.297**	-0.383*	-0.314***	-0.381	-0.155
	(0.210)	(0.124)	(0.207)	(0.099)	(0.236)	(0.125)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm-input FE	Yes	Yes	Yes	Yes	Yes	Yes
Number of firm-inputs	1157	1118	1227	1189	944	921
Number of observations	9983	9673	10554	10258	8042	7869

Notes: See Table 1.

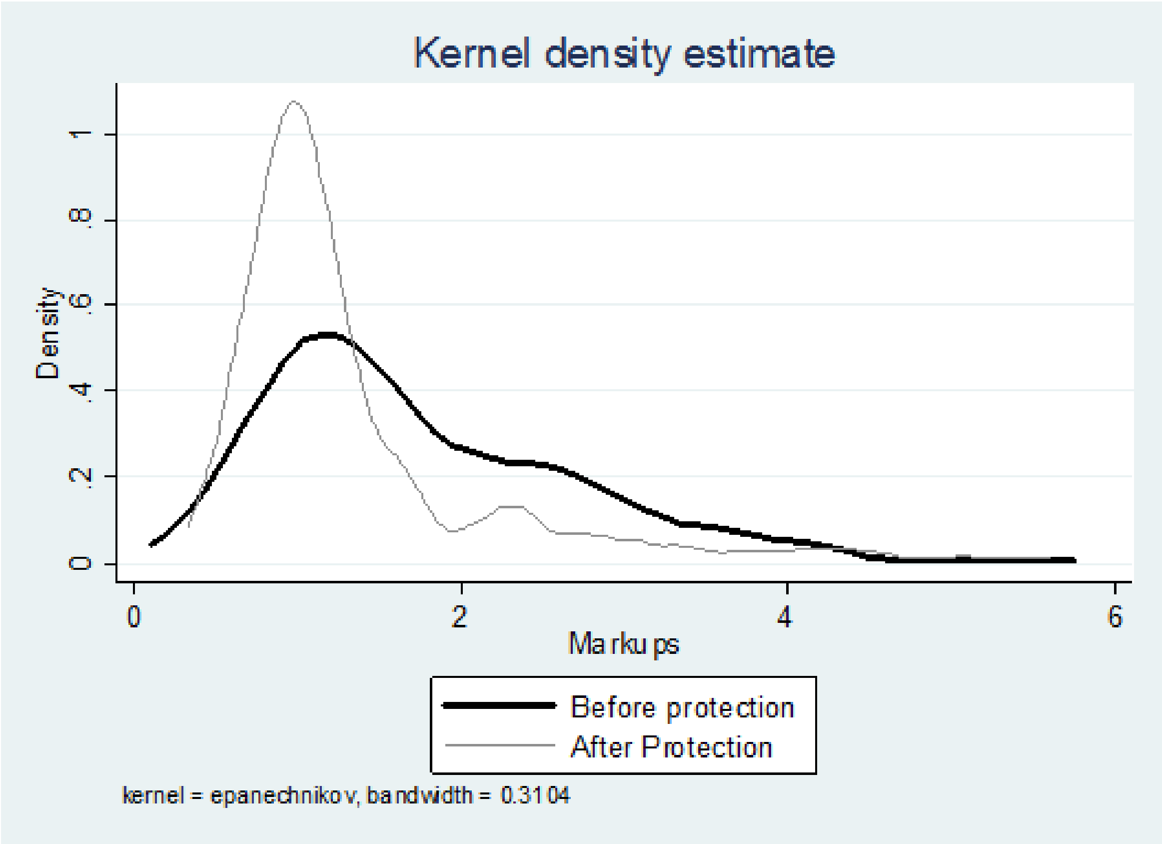
Table C5: Results on the extensive margin of input reallocation

	Complete sample				Reduced sample	
	Input dropped	Input added	Input dropped	Input added	Input dropped	Input added
	(1)	(2)	(3)	(4)	(5)	(6)
Pre AD x TR x T (β_1)	-0.258	-0.407	-0.194	-0.412	0.409	-0.610
	(0.848)	(0.334)	(0.845)	(0.330)	(0.911)	(0.398)
AD x TR x T (β_2)	**-0.003**	**-0.321****	**0.029**	**-0.283***	**0.354**	**-0.267**
	(0.427)	**(0.157)**	**(0.426)**	**(0.155)**	**(0.544)**	**(0.173)**
Post AD x TR x T (β_3)	-0.500	-0.194	-0.517	-0.120	0.023	0.067
	(0.861)	(0.254)	(0.853)	(0.255)	(0.929)	(0.282)
Pre AD x T (β_4)	0.100	0.035	-0.101	-0.287*	-0.044	-0.175
	(0.383)	(0.156)	(0.369)	(0.149)	(0.441)	(0.172)
AD x T (β_5)	**0.103**	**0.188****	**0.153**	**0.175****	**0.215**	**0.184****
	(0.219)	**(0.084)**	**(0.199)**	**(0.076)**	**(0.238)**	**(0.085)**
Post AD x T (β_6)	0.214	-0.154	0.058	-0.021	0.421	0.103
	(0.395)	(0.132)	(0.369)	(0.127)	(0.435)	(0.153)
TR x T (β_7)	-0.395	-0.124	-0.419	-0.152	-0.780*	-0.192
	(0.339)	(0.115)	(0.337)	(0.113)	(0.451)	(0.124)
T (β_8)	0.444**	0.331***	0.456**	0.350***	0.620***	0.466***
	(0.191)	(0.072)	(0.178)	(0.066)	(0.225)	(0.077)
Year FE	Yes	Yes	No	No	No	No
Number of firm-inputs	18389	18389	18389	18389	7564	7564
Number of observations	95274	95274	95274	95274	40793	40793

Notes: ***, ** and * indicate a significance level of 1, 5 and 10%, respectively. Reported standard errors in brackets are cluster robust with clustering at the firm-input level. The table shows results of the regression described by the system of equations (21), estimated with a multinomial logit model and using *no change in input use* as the base outcome. T is a dummy variable that marks firms that are at a certain point in time using protected inputs, including both importers and non-importers. TR marks the treated input. *Pre AD*, *AD* and *Post AD* are one respectively in the year before, during and after protection. The main coefficients of interest are β_2 and β_5 (in bold). β_5 indicates whether firms that use protected inputs increasingly start using/drop unprotected inputs, when protection is imposed. $(\beta_5 + \beta_2)$ indicates whether firms that use protected inputs increasingly start using/drop protected inputs, when protection is imposed. β_2 is the differential effect of protected relative to unprotected inputs.

D Markup Estimation

Figure D1: Markup evolution of firms affected by antidumping protection on inputs



Source: Authors' estimates.

Notes: The figure considers the distribution of average firm level markups in the period before protection and of average firm level markups in the period after the protection date (Kernel density estimates). The markups are estimated, following De Loecker and Warzynski (2012).

Table D1: Output elasticities from a Cobb-Douglas production function

	Labor	Materials	Capital
Food, beverages (NIC 2-digit 15)	0.32	0.53	0.11
Textiles, apparel (17)	0.13	0.88	0.14
Paper, paper products (21)	0.15	0.73	0.17
Chemicals (24)	0.27	0.74	0.002
Rubber, plastics (25)	0.20	0.77	0.05
Non-metallic minerals (26)	0.09	0.49	0.06
Basic metals (27)	0.16	0.72	0.11
Fabricated metals (28)	0.18	0.77	0.11
Machinery, equipment (29)	0.18	0.68	0.29
Electrical machinery (31)	0.09	0.83	0.05
Motor vehicles (34)	0.16	0.74	0.03

Notes: The table reports coefficients of a three-factor Cobb-Douglas production function: labor, materials, and capital. Estimations are performed separately by NIC sector. Only those sectors are included for which the number of observations is sufficiently large to estimate the deflated revenue production function.

Table D2: Estimated markups by sector

	Markup (average)	Standard dev.
Food, beverages (NIC 2-digit 15)	1.50	2.04
Textiles, apparel (17)	1.83	0.83
Paper, paper products (21)	1.78	1.03
Chemicals (24)	1.53	1.11
Rubber, plastics (25)	1.81	1.05
Non-metallic minerals (26)	1.50	1.70
Basic metals (27)	1.05	0.78
Machinery, equipment (29)	1.17	1.00
Electrical machinery (31)	2.78	1.59
Motor vehicles (34)	2.64	1.69

Notes: Markups are estimated with the De Loecker and Warzynski (2012) method. The overall average markup is 1.6 and the standard deviation is 1.3. Only those sectors are included for which the number of observations is sufficiently large to estimate the deflated revenue production function.