Indian antidumping policy and markups of domestic producers*

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Abstract Over recent years, India has become one of the most frequent users of antidumping measures. Indian firm-level panel data at hand, this paper estimates the effects of antidumping protection on markups of domestic import-competing firms. Controlling for the potential endogeneity of antidumping protection by combining nearest neighbour matching techniques with difference-in-difference regressions, we conclude that domestic producers are not able to increase their profitability in the years of trade protection. This result is robust to a variety of specifications, estimation methods and methods to identify protected firms. Consistent with this finding, we also show that unit values of protected goods, sold by domestic producers, do not increase as response to protection. This paper is amongst the first to provide firm-level evidence on the effects of antidumping protection in a developing country.

Keywords: Antidumping policy; Firm-level data; India; Markup; Matching; Policy evaluation; Price-cost margin; Trade policy

JEL classification: F13; L13; L41

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1 Introduction

Until the end of the 1980s, antidumping (AD) policy was almost exclusively applied by the so-called *traditional users* European Union (EU), United States (US), Canada and Australia. However, developing countries have become predominant in the use of AD policy over the recent years (Vandenbussche and Zanardi, 2008). Between 1990 and 2000, at least 40 developing countries adopted an AD law.[1] The share of AD measures imposed by these countries has increased tremendously from 2 per cent prior to the 1990s to 48 per cent in 2012.[2] While the existing empirical evidence on AD mostly focusses on the EU and the US, the empirical literature on AD in developing countries has just started to emerge. In order to assess the increased use of AD by developing countries, however, it is important to learn more about the economic impact of AD in these countries. The economic impact may differ from the one in developed countries as institutional settings and motivations for the use of AD policy are country-specific.[3] Furthermore, countries have considerable scope in the design of AD laws and their application within the GATT rules.

In this paper we investigate the impact of Indian AD policy on domestic producers' markups, calculated as price-cost margins. Using an Indian firm-level dataset, we provide firm-level evidence on the effects of AD policy in a developing country. Markups are a measure of firms' ability to charge prices above marginal cost and are hence an indicator of both market power and profitability. The effect of AD protection on firms' markups constitutes an important building block of the overall assessment of AD protection, which motivates this paper.

An AD tariff is theoretically similar to an import tariff. Static partial equilibrium models of imperfect competition tend to predict a rise in markups due to a tariff, illustrating that tariffs can have an anti-competitive effect (Helpman and Krugman, 1989). In the case of a domestic monopolist that faces import competition in its domestic market, an import tariff always raises the domestic price. Provided the tariff is high enough, it may even allow the monopolist to sell its good at the profit-maximizing monopolist price. A similar result is obtained if imports are considered as imperfect substitutes for the good produced by the domestic monopolist, given that the increase in the foreign price due to the tariff raises demand for the good produced by the domestic firm, which in turn besides raising sales may also raise prices and, hence, price-cost margins. An increase of markups due to a tariff can also be shown to occur in the more realistic

[1] This number was derived from Table 1 in Zanardi (2004a) who gives a comprehensive overview of the proliferation of AD laws. The classification of developing countries is taken from the International Monetary Fund, http://www.imf.org/external/pubs/ft/weo/2014/01/weodata/groups.htm#ae [17 March 2014].

[2] The first number comes from WTO (2009, p.139). The second number was calculated based on the AD statistics available from the WTO webpage.

[3] Bown (2008) provides evidence for substantial heterogeneity in the determinants of AD use at the industry level across countries.

case of domestic oligopolies both if domestic firms act in a non-cooperative or a collusive way. The same result, higher prices and less competition due to trade restrictions, are equally obtained in partial equilibrium intra-industry trade models (Brander, 1981; Brander and Krugman, 1983).

The more recent theoretical literature derives similar predictions. Devereux and Lee (2001) show in a dynamic general equilibrium model in which a small number of firms interact strategically with one another that more competition through imports comes along with lower markups. While they only compare the extreme cases of autarky and free trade, their analysis suggests that any kind of restriction to trade can likely be associated with higher markups. In a large set of trade models that assume monopolistic competition including the one of Melitz (2003), markups are constant and hence not affected by trade policy. This is due to the common assumption of preferences that are characterized by a constant elasticity of substitution (CES). Under quadratic preferences instead, Melitz and Ottaviano (2008) demonstrate that unilateral trade liberalization induces lower markups, at least when assuming away firm relocation effects. In their model, a unilateral increase in trade protection, in contrast would result in more market power and increased markups. Similar results are obtained by Feenstra and Weinstein (2010) who assume translog preferences.

Despite these relatively uniform theoretical predictions, there are some countervailing forces that may dampen or even suppress a rise in markups driven by an import tariff. First of all, there could be import diversion due to the fact that AD measures are discriminatorily imposed, or entry of new domestic firms into the market. In other words, other suppliers of the good might step in for the supplier whose imports are kept out of the Indian market due to the AD measure. Moreover, there is also the possibility of tariff jumping, so that foreign firms start to shift their production physically to India in order to get around the AD measures. Finally, if AD measures are imposed on products that are inputs into production, importers of these inputs have the option to use less of them and move towards production activities that are less intensive in these inputs (Vandenbussche and Viegelahn, 2014). This is likely to be relevant for India, whose AD policy is almost exclusively applied to intermediate inputs rather than to final goods. It can prevent domestic producers from raising prices, given the only limited increase in demand for domestically produced inputs, which arises as a consequence of input switching.

Given these ambiguities, the impact of AD protection on markups ultimately appears to be an empirical question. Konings and Vandenbussche (2005) find for the EU that domestic firms' markups increase significantly during periods of AD protection. Nieberding (1999) provides three case-studies on the effect of US AD law on market power of domestic firms and observes as well a positive impact. In contrast, Blonigen et al. (2007) do not find any effect of AD protection on the market power of US steel producers. These different results illustrate the need for further empirical evidence. Particularly for developing countries, the impact of AD protection on markups has not been studied much.

India is a relevant country to focus on as it is currently the main user of AD policy worldwide.[4] After the adoption of an AD law in 1985, India initiated its first AD case in 1992. While the number of cases was still relatively low until 1998, the number of initiations and measures imposed by Indian authorities drastically increased from the end of the 1990s onwards. In nine of the twelve years between 2001 and 2012, India was the country with the worldwide largest number of AD case initiations, according to statistics provided by the World Trade Organization (WTO). However, while there exists a large body of literature on Indian trade policy that is concerned with the effects of the Indian trade liberalization reforms initiated in 1991, the literature on Indian AD policy is quite new.[5] We therefore believe to make a contribution not only to the empirical trade literature in general, but also to the literature on India's trade policies in particular.[6]

The rest of this paper is organized as follows. The next section describes the data. Section 3 outlines the empirical methodology that is applied in order to identify the effect of AD protection on markups. Section 4 discusses results of the estimations, provides a number of robustness checks and shows evidence on the effect of AD protection on unit values. Section 5 concludes.

2 Data

In this paper, we mainly draw from two databases. The first database, *Prowess*, contains Indian firm-level data that is collected by the Centre for Monitoring Indian Economy (CMIE), a private company based in Mumbai. *Prowess* reports information from balance sheets and income statements of Indian firms. It contains only data for medium and large size enterprises, a restriction that needs to be taken into account when interpreting our results. However, Goldberg et al. (2010a) who study the response of domestic variety to trade liberalization and use the same dataset report that *Prowess* contains data on firms that account for 60-70 per cent of organized industrial activity in India, 75 per cent of the Indian government's cooperate tax revenue and 95 per cent of revenues from excise duties, which gives us confidence in the dataset coverage. Firms are assigned to industries according to the National Industrial Classification (NIC) which is a 5-digit

[4] Figure 1 below shows the evolution of the number of AD case initiations and measures imposed by Indian authorities. Figure 2 illustrates the number of AD measures in force over time.

[5] See, for example, Narayanan (2006), Baruah (2007), Ganguli (2008), Malhotra and Malhotra (2008) and Aggarwal (2010) for recent papers on Indian AD policy. De Loecker et al. (2012) looks into the impact of Indian trade liberalization on Indian firms' markups.

[6] According to Vandenbussche and Zanardi (2010), the trade-depressing impact of AD measures in India has been far from negligible, largely offsetting the impact of the trade liberalization reforms that lowered the average import tariff from more than 90 per cent in 1990 to around 30 per cent in 2000 as reported by Topalova (2007).

industry classification employed by Indian statistical agencies.[7] For this paper, we use data on firms' sales, raw material expenses, expenses on power and fuel, salaries and wages and net fixed assets. Wherever necessary, nominal values are deflated with a sector-specific wholesale price index, published by the Office of the Economic Advisor to the Ministry of Commerce and Industry. While the database contains data for 1989-2007, the examination period is restricted to 1999-2007, as salaries and wages are to a large extent only available from the end of the 1990s onwards. We end up with an unbalanced panel of 5226 manufacturing firms with on average 2992 observations of markups in each year of the examination period. Some descriptive statistics of the *Prowess* data are given in Table 1.

For the second database, hereafter referred to as AD database, we use the World Bank's Global Antidumping Database (version *Q4_2011*) (Bown, 2012), complemented with additional information from Indian national sources. For each case, the Indian government publishes notifications on initiation, preliminary and final findings and on the imposition of AD measures in the government journal *Gazette of India*. Our database draws upon the Global Antidumping Database as well as on the notifications that are mostly made available on the official websites of the Indian Ministry of Industry and Commerce and the Ministry of Finance. For each AD case we collect the name of the product for which protection was filed and the corresponding HS codes at the 6- or 8-digit level as reported in the notifications. Our databases also includes target countries, relevant dates as well as measures recommended and imposed if any. For the cases initiated in 1992-2007, we also collect the names of domestic producers that file or support an AD petition, or are otherwise mentioned in the AD notification as belonging to the domestic industry.[8] These producers are reported in the AD notifications to account on average for a production share of at least 77 per cent in their industries.[9]

[Table 1]

[Table 2]

[Table 3]

[Table 4]

[7] At the 4-digit level, the NIC classification (Rev. 1998) corresponds one-to-one to the internationally used ISIC (Rev. 3) industry classification.

[8] By drawing directly upon information provided in the Indian AD notifications, we are able to identify more firms than if we just used the Global Antidumping Database.

[9] The AD notifications contain information on this share, given that the Indian AD law — in line with WTO regulations — stipulates that firms that file for protection or support the application should together account for more than 25 per cent of Indian production. In addition, they should account for more than 50 per cent of the total production of firms supposing or explicitly opposing protection.

[Table 5]

[Figure 1]

[Figure 2]

Tables 2-5 and Figures 1-2 provide some descriptive statistics of the AD database. On the whole, 645 AD cases were initiated in 1992-2011 of which 491 resulted in protection and 146 did not, such that no AD measures were imposed.[10] Most cases were initiated against China (146), the European Union (49) and South Korea (48). The vast majority of cases (62.9 per cent) is initiated in the chemicals industry, followed by basic metals (13.6 per cent) and textiles (3.4 per cent). The 500 AD cases that were initiated in 1992-2007, our period of investigation, follow a similar distribution across case outcomes, target countries and sectors.

We are facing the task to match the AD database with the database of Indian firms in order to identify those firms that are involved in AD cases. This is not straight-forward, given that the two databases in their original form do not have a common identifier. On the whole, we use five different methods to identify protected firms and will henceforth refer to these methods respectively as *frmpr*, *frmpr2*, *frm*, *nic* and *hsnic* method. All of these methods are used in order to ensure that our estimates are robust to the way how the two databases are matched.

The first two methods make use of the fact that *Prowess*, in addition to the firm-level data described above, also has a module with firm-product level data on firms' product sales. For 4618 of the 5226 manufacturing firms for which we have firm-level data, we have a list of products the firm sells, together with information on respective values and quantities. However, this information is not standardized, such that products are not reported as product codes, but in the form of product names only. The level of detail in reporting as well as the spelling of product names differ across firms. To overcome this difficulty, we apply a word-based matching algorithm that matches AD and firm-product level data by product name. This algorithm defines for each of the products that appear in an AD case relevant words or word fragments. For each product, we then define a matching rule that identifies theses words, word fragments or combinations of them in the firm-product level data.[11] Through the algorithm, we are able to identify 404 firms that sell a product at least once involved in an AD case between 1992 and 2007. Out of these 404 firms, there are 333 firms that sell a product at least once involved in an AD case in which protection is granted. The first method (*frmpr*)

[10] At the time the AD database was compiled, the outcome was still unknown for 8 AD cases.
[11] The matching algorithm is implemented in analogy to the one described in Appendix 2 of Vandenbussche and Viegelahn (2014) for raw material inputs.

counts all these firms as affected by an AD case. However, some of the firms have missing firm-product level data in the year in which the AD case is initiated, so we cannot be sure whether they sell the product in the year in which AD measures are imposed. As second method (*frmpr2*), we therefore only consider those firms that, in the AD case initiation year, report to sell a positive amount of the product that is involved in the case.

As third method (*frm*), we directly extract the names of domestic producers from the Indian AD notifications and identify them in the firm-level database. We do this manually taking into account variations in spellings and possible changes of firm names and are able to identify in the firm-level data almost 70 per cent of all the producers that are mentioned in the notifications.[12] As there are possibly more firms that are affected by AD cases, we check which 5-digit NIC industry code *Prowess* assigns to the firms that are mentioned in the notifications. The fourth method (*nic*) considers all other firms that belong to the same industry as also involved in the AD case. The last method (*hsnic*) makes use of the HS product codes that are contained in the Global Antidumping Database for each case. We match these codes to the NIC industry classification at the 4-digit level using several concordance tables published by the United Nations.[13] All the firms that are assigned to the matched NIC industry are then considered to be involved in the respective AD case.

After having defined firms that are affected by AD policy through each of these five methods, we obtain five groups of firms. For each of these five groups, we create an AD protection profile which contains information on whether a firm is protected or not by an AD measure in a certain year. We count a year as *protection year* if there is an AD measure in place during at least six months of that year. The resulting protection profiles are then used in our regression analysis.

Besides *Prowess* and the AD database, we also use data on Indian imports from UN Comtrade. The import penetration ratio at the industry level is calculated as industry imports over the sum of industry imports and domestic industry sales, where industry sales are aggregated from *Prowess*. This is likely to yield an upward biased measure of import penetration, given that our firm database is not a census. However, this is unavoidable as we do not have other data on industry sales at hand. Tariff data stem from the *Integrated Data Base* (IDB) of the WTO. Basic summary statistics for import and tariff data are reported in Table 6.

[Table 6]

[12] If no direct match is found at first hand, we try to find some information on firms' webpages if the firm possibly changed its name. If this is the case, we try to identify the firm in *Prowess* under its new name.

[13] Most studies using Indian data, for example Goldberg et al. (2010b), rely on a concordance table by Debroy and Santhanam (1993) which matches HS to 3-digit NIC codes. We match at the more disaggregate 4-digit level using the fact that NIC (Rev. 1998) matches one-to-one to ISIC (Rev. 3) at this level. HS can be matched to ISIC with the available concordance tables, where few AD cases were assigned to more than one NIC sector. The matching was checked manually for correctness.

3 Empirical methodology

3.1 Measuring markups

Markups as measure for the profitability and market power of firms are not directly observable as we do not have firm-level data on price P and marginal cost C at hand. Markups have to be indirectly inferred where different methods are at our disposal. One popular method that is discussed by Tybout (2003) and used in our paper is the calculation of the price-cost-margin (PCM) as proxy for the Lerner index of monopoly power,

$$PCM_{it} = \frac{P_{it}Q_{it} - P_{M,it}M_{it} - W_{N,it}N_{it} - P_{F,it}F_{it}}{P_{it}Q_{it}} = \frac{P_{it} - C_{it}}{P_{it}}, \tag{1}$$

where $P_{it}Q_{it}$ are sales of goods, $P_{M,it}M_{it}$ are material costs, $W_{N,it}N_{it}$ is the wage bill and $P_{F,it}F_{it}$ are expenses on fuel and energy of firm i in year t. All variables enter the PCM calculation in nominal terms. The PCM is calculated as a firm-specific measure, even though the degree of profitability may vary across the product markets in which the firm is operating. It may also vary geographically, for example across Indian states, and be different in the export market. In case of a single-product firm which is only operating in a single product market, the firm-level PCM provides an average measure of the firm's profitability in that market. In the case of multi-product firms, the PCM as calculated in equation 1 provides an average measure of a firm's profitability across different product markets.

If we assume that all short-run marginal costs are covered by labour, material and energy costs and that marginal costs can be approximated by average costs per unit of output, the second equality in (1) holds. The latter assumption in turn implicitly presumes constant returns to scale (CRS) in production. If an industry is composed of only one or few large firms, the CRS assumption is less likely to hold. Such an industry structure may arise from the presence of increasing returns that make it beneficial for firms to operate at a large scale. If we calculate the market share as the share of firms' sales in total sales of all firms assigned to the same industry and, in addition, examine the number of firms operating in an industry in the *Prowess* database, we find that markets are mostly not served only by a few large firms.[14] When restricting the sample to those industries that file for AD protection most frequently, we find on average an even more scattered structure, suggesting that the PCM may in fact not be too far away from the "true" Learner index in these industries.

[14] Firms' market shares take on a median (average) value of 0.09 (0.5) per cent and a maximum value of 45 per cent, and the average number of firms per industry is 238, if we define markets according to the NIC classification at the 2-digit level. Defining the market more narrowly at the 4-digit level, the median (average) value is 0.4 (3.0) per cent, while the average number of firms in an industry is 47.

3.2 Selecting control groups

We are interested in the *average treatment effect on the treated*, where treatment corresponds to AD measures imposed. We face the common problem encountered in the non-experimental policy evaluation literature: we do observe treated, protected firms only when they get treatment, but not in the counterfactual situation when they do not get any treatment. In other words, we would like to know what would have happened if the protected firm had not been protected, but this information is not available to us.

If AD measures were assigned randomly to firms, such that protected and unprotected firms had on average the same characteristics and differed only by the fact that protected firms are treated while unprotected firms are not, the PCM trajectory of all unprotected firms could serve as a counterfactual. In reality, however, AD protection is unlikely to be a random policy. It may be endogenous as two stages of selection are involved before a firm gets protection. In the first stage, firms self-select themselves by filing a petition for AD protection. In the second stage, the government decides upon whether it grants protection or not, based on its injury and dumping findings. At the same time, it can occur that firms withdraw their petition.

The first control group that we consider is the group of firms that are involved in termination cases; these are firms that belong to a sector for which the Indian AD authorities decide not to grant AD protection or firms that withdraw their petition after applying for protection. We check whether we can find a change in markups after the year of initiation of a termination case and compare the results with the ones for the treated group of firms for which AD measures were imposed. The choice of this control group is likely to eliminate the first stage self-selection bias. On the other hand, however, the negative AD ruling by the government or the decision to withdraw a case is still likely to be non-random. Moreover, also firms in termination cases might be protected from foreign competition and experience treatment. Firms that, for example, withdraw their petition might find alternative ways to influence the degree of competition from foreign producers (Prusa, 1992; Zanardi, 2004b).

Therefore it is essential to find an alternative second control group. We follow the microeconometric policy evaluation literature and draw upon matching techniques (Heckman et al., 1998). Matching methods being originally applied to cross-sections of data have recently started to be used as well for panel data.[15] The use of matching techniques to tackle policy endogeneity avoids problems related to the use of other policy evaluation methods as discussed by Blundell and Costa Dias (2009).

For the matching process, we assume that all differences between protected and unprotected firms that

[15] For example, see De Locker (2007) or Konings and Vandenbussche (2008).

affect treatment assignment, markups and their evolution can be fully captured by a vector of observable pre-treatment characteristics, making use of the relatively rich dataset that was described in the previous section. Our objective is to assign to each protected firm an unprotected "twin" firm that is as similar as possible in these observables to the protected counterpart prior to protection. Rosenbaum and Rubin (1983) suggest to summarize the multi-dimensional vector of pre-treatment characteristics within a one-dimensional index, the propensity score p_{it}, and therewith reduce the number of variables that enter the matching function to one in order to overcome the "curse of dimensionality". To obtain the propensity score, we estimate the following pooled probit model on the sample of treated firms and firms that never get protection as potential control group. The group of treated firms is restricted to include only those firms that get protection from an AD case initiated between 2001 and 2007, but not before. This allows us to match on pre-treatment characteristics, considering the limited period from 1999 to 2007 for which firm-level data are available:

$$\begin{aligned} Pr\{INIT_{it} = 1\} = \Phi(&\beta_0 + \beta_1 PCM_{i,t-1} + \beta_2 PCMDIFF_{i,t-1} + \beta_3 IMPGWTH_{j,t-1} \\ &+ \beta_4 IMPP_{j,t-1} + \beta_5 LOGCAP_{i,t-1} + \beta_6 TAR9600DIFF_j + \beta_7 GDPGWTH_t). \end{aligned} \tag{2}$$

The dependent variable $INIT_{it}$ equals one if a firm i applies for the first time in year t successfully for protection and zero otherwise. $\Phi(.)$ is the normal cumulative distribution function, j is an industry index at the NIC 4-digit industry level. The independent variables are required to capture all characteristics that have an impact on both PCM and the probability of getting protection. The selection of characteristics takes into account findings of the recent literature.

First of all, we include the price cost margin, PCM, and its annual change, $PCMDIFF$, into the probit model. If the PCM follows the same trend before protection for both groups of firms, we may expect the same trend to persist for both groups of firms if protection does not have any effect on the PCM. Furthermore, market power of firms as proxied by the PCM level may be relevant for the decision of the Indian government to grant protection as shown by Baruah (2007). We as well include real import growth $IMPGWTH$ which is a factor that the Indian government seems to consider when it establishes the link between dumping and injury as apparent from the Indian AD notifications. $IMPP$ is the import penetration ratio which is a factor that has been shown for other countries to influence AD policy decisions (Konings and Vandenbussche, 2005; Blonigen and Park, 2004). As a measure of firm size, we include $LOGCAP$, the logarithm of deflated net fixed assets of a firm. $TAR9600DIFF$ is the difference between the average applied MFN tariff levels of 2000 compared with 1996. Bown and Tovar (2011) show that it is especially firms in those sectors that experienced a large decrease in import tariffs during the Indian trade liberalization period that obtain AD protection. Including this variable into the matching process, we are aiming at identifying those firms as control firms that are in sectors in which trade was liberalized to a similar extent as in treated sectors. Finally, $GDPGWTH$ stands for real GDP growth and controls for aggregate business cycle fluctuation which are likely to be an important determinant of protection as shown by Bown and Crowley (2013, Forthcoming). All independent variables except GDP growth are introduced with a lag, taking into account that governments grant protection based on past firm performance and minimizing the risk of endogeneity due to ex-ante behavioural adjustments of firms or trade effects in anticipation of the AD measure.

Given the propensity score, we apply nearest-neighbour matching where we choose for each treated firm a single nearest neighbour. When using *frmpr*, *frmpr2* and *frm* as method to identify treated firms, we impose as a restriction that the match should take place in the year in which the AD case is intitiated.[16] In order to guarantee unbiased results, we restrict our sample to the common support of the propensity score. Matching is done without replacement such that a firm is dropped from the dataset once it is matched and cannot be matched to another treated firm. Considering each firm only once reduces the variance of our estimates and avoids that two different firm-year observations belonging to the same firm are matched to two different treated firms. To guarantee that results do not depend on the matching order, we randomly generate this order as proposed by Caliendo and Kopeinig (2008).

We end up with a control group of matched firm-year observations where we consider the year in which a firm is matched as the "hypothetical" year of initiation of an AD case. With difference-in-difference regressions, we will check whether the PCM of these firms changes signficantly in the years afterwards and compare this to the evolution of markups before and during protection of protected firms.

3.3 Estimating the effect of protection

In order to estimate the *average treatment effect on the treated*, we use a difference-in-difference approach and estimate the following regression equation on the sample of observations for two groups of firms, those that get protection and each of the two control groups:

$$PCM_{it} = \alpha_0 + \alpha_1 AD_{it}\ X\ TR_i + \alpha_2 AD_{it} + \alpha_3 \left(\frac{K_{it}}{P_{it}Q_{it}}\right) + \alpha_4 \left(\frac{P_{it}Q_{it}}{\sum_{i\in j} P_{it}Q_{it}}\right) + \epsilon_t + \epsilon_i + \epsilon_{it}. \tag{3}$$

[16]For the other methods, more firms need to be matched and, hence, we do not impose this restriction in order to ensure that the matching works well.

ϵ_t is a year-specific fixed effect that is accounted for with year dummies and controls for macroeconomic shocks, including shocks to aggregate demand, that have an impact on markups of firms in all industries.[17] ϵ_i is an unobserved firm-specific fixed effect and ϵ_{it} stands for an idiosyncratic error term. TR_i is a treatment dummy that marks protected firms. AD_{it}, for treated firms, is one if firm i is protected by an AD measure in year t and zero otherwise. For firms in the termination control group, AD_{it} is one in the years after the initiation of the case. The regression then compares the evolution of markups in treated firms before and during protection to the evolution of markups in the termination control group before and after the termination case is initiated. For firms in the matched control group, AD_{it} is one in the years after the matching year. Regressions with this control group compare markup trends in treated firms to those in matched control firms before the firms are matched (when markups by construction follow a similar trend) and afterwards. α_1 then corresponds to the differential impact of AD measures that we are interested in.

Following Tybout (1996), Roberts (1996), Grether (1996), Konings and Vandenbussche (2005) and others, we include the capital over sales ratio $\frac{K_{it}}{P_{it}Q_{it}}$ as control. As illustrated by Tybout (2003) the impact of AD protection should be zero after controlling for capital over sales if industries are perfectly competitive. Due to potential endogeneity problems, we instrument the capital-sales ratio with its past values at $t-1$ and $t-2$. To control for scale effects, we equally follow the literature and add the market share of firm i in industry j, $\left(\frac{P_{it}Q_{it}}{\sum_{i\in j} P_{it}Q_{it}}\right)$, as additional regressor on the right-hand-side. The market share is calculated as the share of firms' sales in total sales of all firms assigned to the same NIC 4-digit industry in the *Prowess* database. The major product sold by the firm typically belongs to that industry, given that firms are assigned to an industry if more than half of its sales are derived from products belonging to this industry.[18] Due to potential endogeneity problems, we instrument the capital-sales ratio and the market share with their past values at $t-1$ and $t-2$.

We also run regressions in which we control for industry concentration, measured through the Herfindahl index that is calculated on the basis of firm-level sales data by NIC 4-digit industry. Finally it could be that any impact of AD protection is offset by a lower level of "conventional" import tariffs (Bown and Tovar, 2011). While we control for past trade liberalization already in the nearest neighbour matching procedure (see section 3.2), we also control directly for the level of the applied MFN tariff, when running the regression

[17] We also considered the introduction of sector-year dummies which would take into account differences in aggregate demand trends across sectors. This, however, would take away many degrees of freedom and force us to drop some observations from the sample, which is why we decided to stick to year dummies.

[18] This classification is based on data available as of September 2008. If no industry accounts for more than half of a firm's sales, the firm is classified as *Diversified* and hence is not part of the sample of manufacturing firms that we consider in this paper. Note that in the original data only 64 out of more than 20,000 firms are classified as *Diversified*, which suggests that firms in the database – including multi-product firms – typically have their focus on one industry only.

on an alternative specification of equation 3.[19]

4 Results

4.1 Pooled probit model and nearest neighbour matching

We start by discussing the results of the matching procedure as outlined in the previous section. The results of the pooled probit estimation introduced in equation 2 are reported in Table 7. Although the regression itself is not in the focus of our paper, we get some confidence about the choice of variables when looking at the estimated coefficients. If firms are in sectors that experienced a decrease in import tariffs between 1996 and 2000, they are more likely to get protection which is in line with the findings of Bown (2011). Furthermore, firms with more market power as measured with the PCM are more likely to successfully apply for protection. It is also particularly firms with decreasing markups that apply for protection, in line with the injury condition that needs to be satisfied according to the AD law to get protection. Moreover, it is larger firms that are more likely to file for protection. For import growth, the result is somewhat in contrast to what we would expect with more import growth leading to a lower likelihood to file for protection. This may be related to the fact that we measure imports only at the relatively aggregate NIC 4-digit level. For import penetration which is measured at the same level of aggregation, results are also rather mixed. For *nic* and *hsnic*, where all firms in a certain sector are considered as protected, results on imports might be driven by only a few sectors. This is because a large number of sectors is excluded from the regression due to the condition that control firms should not be involved in any AD case initiated in 2000 or before. Finally, most regressions associate lower GDP growth with a higher likelihood to get protection.

Figure 3 shows the kernel density estimates of the propensity scores before and after the matching for the five methods. Although there are large differences in the distributions before matching, the common support restriction is never binding. In other words, there are no observations for treated firms outside the common support to be dropped. After the matching, the estimated density functions are almost identical. In Table 8, we report means of the matching arguments for treated and matched firms and perform t-tests for the inequality of these means. For the methods *frmpr*, *frmpr2* and *frm*, we cannot reject the null that the independent variables' means of treated firms and firms in the selected control group are equal which confirms

[19] Data on applied MFN tariffs are only available from the WTO's *Integrated Data Base* (IDB) for 2000-2003, 2006 and 2007, but not for 1999, 2004 and 2005. Since the use of data on applied MFN tariffs in regressions hence either requires the drop of a large part of the sample or the use of imputation techniques to fill the data gaps, we do not include this variable in all specifications for which results are reported.

our success in matching. Only for *nic* and *hsnic*, there remain some significant differences in means, which may cause a bias that needs to be taken into account when interpreting our results on markups. However, the matching is successful also here in selecting control firms that are on average more similar to treated firms than the potential control group that consists of all potential control observations.

[Table 7]

[Figure 3]

[Table 8]

4.2 Antidumping and markups: difference-in-difference regressions

Now let us turn to the results of our main interest, the estimation of the effect of AD protection on markups. Results of fixed effect (FE) instrumental variable (IV) regressions are reported in Tables 9 and 10 for all five methods — *frmpr*, *frmpr2*, *frm*, *nic* and *hsnic* — with which we identify protected firms. Results are obtained from respectively using firms from termination cases and matched firms as control group.

[Table 9]

In all regressions, we test for the validity of instruments that are used for the capital-sales ratio and the market share. As we use more than one instrument, considering the lagged values of the capital-sales ratio and the market share up to a lag of 2, we can test overidentifying restrictions. In nearly all regressions, Hansen's heteroskedasticity robust J test cannot reject the exogeneity of instruments with respect to the PCM. We as well compute the Cragg-Donald F-Statistic in order to check for weak identification and find reasonable values that are mostly above the critical ones derived by Stock and Yogo (2005).

[Table 10]

When using firms involved in termination cases as control group, the estimated coefficient of interest is either insignificant or significantly negative (columns 1 and 5 of Table 9), which is a result that seems surprising at first glance. If we believe that this group of firms is a valid control group, these results would suggest that domestic producers' profitability goes down when AD measures are imposed. In other words, trends in markups of firms involved in termination cases tend to evolve more favourably after the initiation of a case than trends in markups of firms that are protected with an AD measure. However, as discussed above, firms involved in termination cases might in fact experience treatment as well, even though an AD measure is absent, which would cause a bias in our results. As derived and shown by Prusa (1992) and Zanardi (2004b), firms may benefit from the mere initiation of an AD case. Such an initiation can be used as a “collusive device” and foster price agreements between domestic and foreign producers in the interest of the former. If this holds for India, then the impact that is found is not any more too surprising. If we assume that domestic producers act in their best interest when negotiating about prices with foreign producers, the outcome of such an agreement might be superior to the outcome of an AD measure. This is because — according to the so-called *lesser duty rule* in the Indian AD law — the Indian government is obliged to set the AD duty to the minimum of dumping and injury margin, a restriction that producers do not have when negotiating a price agreement.

Therefore we concentrate on the regressions in which we use matched firms as a control group. Firms that are matched through the nearest-neighbour matching procedure described before have similar pre-treatment characteristics as protected firms. Under the assumption that we considered all relevant factors in the matching procedure, this control group should help us obtaining unbiased estimates. Results are reported in Table 10 and reveal that there is no significant impact of AD protection on the PCM of protected firms in any of the regressions that use the matched control group as benchmark of comparison. Moreover, estimated coefficients are relatively small in most regressions which suggests that it is more likely due to the true absence of a considerable impact than due to the lack of statistical power that no impact is found. Hence, when using matched control firms, we do not find any significant effect of AD protection on producers’ PCM, based on difference-in-difference regressions.

In Tables 11 and 12, we show results after introducing additional control variables into the regression, still using matched firms as a control group. The regressions specified in Table 11 include the Herfindahl index, a measure for industry concentration that is calculated on the basis of firm-level data by NIC 4-digit industry. Usually, industry concentration tends to be associated with imperfect competition, which in turn can cause markups to be higher at the industry-level. However, this result has been shown to not hold up for the Indian manufacturing sector (Mishra, 2008). Moreover, it is less clear how higher industry concentration affects markups at the firm-level, given the presence of firm entry and exit which we cannot observe in our data. For example, there could be firm exit due to a decline in demand which ceteris paribus increases industry concentration as measured with the Herfindahl index, but is likely to in fact decrease markups.

In line with this argument, results do not suggest that there is a positive relation between the Herfindahl index and firm-level markups. For two specifications (columns 2 and 5 of Table 11), we find a significantly negative coefficient. In any case, the effect of AD protection remains insignificant, also when using the Herfindahl index as a control variable. This insignificance is only shown for *frmpr*, *frmpr2* and *frm*, but it also holds when using *nic* or *hsnic* as methods to identify treated firms.

[Table 11]

While we ensure to compare protected firms with control firms that experienced a similar degree of trade liberalization as protected firms between 1996 and 2000 (see section 3.2), Table 12 introduces the applied MFN tariff directly into the regression. A potential impact of AD protection could be offset by a simultaneous decrease in conventional import tariffs. The regressions reported in columns 1-3 use actual data, where the years 1999, 2004 and 2005 drop out of the sample due to the lack of data on applied MFN tariffs for these years. In the regressions results that are shown in columns 4-6, we impute the missing values through linear interpolation for these three years. Regardless of whether we impute or not, we tend to find that a decrease in "traditional" import protection lowers markups and hence reduces the profitability of firms, which is as expected. More specifically, a decrease of the applied MFN tariff by 10 percentage points reduces markups by around 0.02-0.03 according to the results in which the impact is found to be significant. We still fail to find an effect of AD protection on markups in all regressions. We equally do not find any sign for an effect of AD protection in the regressions that rely on *nic* or *hsnic* as methods to identify treated firms.

[Table 12]

Finally, we investigate whether the impact of AD protection is different in low-growth-periods relative to high-growth periods. It is well-documented in the literature that trade protection tends to be applied anti-cyclically, which is also true when focusing on temporary trade barriers imposed by emerging economies (Bown and Crowley, Forthcoming). This suggests that governments consider trade protection as a particularly effective policy in low-growth periods. We therefore use the GDP growth rates reported in the IMF's *World Economic Outlook* April 2014 to split our examination period 1999-2007 into five low-growth years (2000-2004) and four high-growth years (1999, 2005-2007). Then we construct a low-growth dummy variable that is one in the five low-growth years and zero in the four high-growth years. The effective threshold below which we consider a year as low-growth year is then around 8 per cent. In Table 13 we document that the impact does not vary significantly for these two growth environments. The interaction *AD x TR x Low* *growth dummy* is insignificant in all regressions.

[Table 13]

4.3 Robustness checks

In this subsection, we run various robustness checks.[20] In a first robustness check, we control for the persistence of markups over time and use dynamic panel estimation techniques, similar to Konings and Vandenbussche (2005). More specifically, we apply the Arellano and Bond (1991) difference GMM estimator, first proposed by Holtz-Eakin et al. (1988). This means that we estimate equation 3 in first differences with the lagged dependent variable as additional regressor. The lagged dependent variable, the capital-sales ratio and the market share are instrumented with their lagged values at $t-2$, since these instruments are not correlated with the first differenced error term.[21] We adjust for small sample size and report cluster-robust standard errors on the basis of t-statistics.

Table 14 shows the results of our estimations, when using matched firms as control group. Hansen's J-test does not reject the validity of instruments. The absence of second order serial correlation is equally not rejected, which confirms the validity of our model choice. With the exception of one regression, we do not find a significant impact of AD measures on producers' markups. Only when using *hsnic* as method to identify treated firms (column 5), we find a weakly significant negative impact, which in terms of magnitude is small. Even though results are not reported, we do not find a significant impact when introducing the Herfindahl index and the applied MFN tariff as additional control variables into the Arellano and Bond (1991) estimation. This by and large confirms previous results in which we did not explicitly take into account markup dynamics.[22]

As further robustness check, we try out two alternative matching techniques. First, we match the three nearest neighbours instead of just the nearest neighbour to protected firms. This could lower standard errors in the regression and, hence, lead to significant results. We ensure that pre-treatment means of treated and matched control firms are still similar. Table 15 reports the results for regressions that were again run with the Arellano-Bond estimator described above (columns 1-3). We still do not find any significant impact of

[20] Results that are referred to but not directly reported in the paper are available upon request.

[21] We also considered including instruments with further lags. Too many instruments relative to observations, however, can overfit endogeneous variables and lead to biases in the coefficient estimates of the model (Roodman, 2009), which is why we opted for a more parsimonious choice of instruments.

[22] We also run the same type of regression on the sample of treated firms and firms involved in termination cases. Results are similar to those that were reported in the previous section.

AD protection on markups.

[Table 14]

Second, there could be unobserved industry characteristics that we do not control for when estimating the propensity score. Such characteristics could lead to a bias in our results if they have an impact on the evolution of firms' markups and the decision to grant AD protection. To address this concern, we introduce as an additional restriction into the matching process that the matched control firm shall belong to the same NIC 2-digit industry as the treated firm, which reduces the risk of such a bias. We again ensure that the balancing property of the propensity score holds despite this restriction and find this to be the case with one exception for *frm*. Besides this exception, pre-treatments means of treated and selected control group are not significantly different from each other. Table 15 (columns 4-6) reports the results. In line with previous findings, we still do not detect any significant impact of AD measures on domestic producers' PCM.

[Table 15]

Next, we do some robustness checks on the way how markups are constructed and exclude expenses on fuel and energy, which are rarely considered in the literature that uses the PCM. We then re-run the matching procedure, ensure that the balancing property holds and run regressions using this alternative definition of markups. Results are reported in column 1-3 of Table 16, where we still do not find any impact of AD protection on the PCM. In columns 4-6, the same table reports results from regressions in which, besides firm-level fixed effects, we only include year dummies as control variables and use standard OLS panel FE estimations. This specification does not lead us to different conclusions. Although not reported, we also find qualitatively similar results when estimating equation 3 without year dummies.

[Table 16]

Another concern is that the average estimate could be insignificant, but hide an effect that occurs in only one of the years AD measures are in force. Equally, there could be an anticipation effect (Vandenbussche and Viegelahn, 2014). In order to investigate the timing of a potential effect, we would therefore like to split up the average impact into an impact in the year before protection is imposed and an impact in the first, second, etc. year of protection. Given that the time dimension of our sample is relatively short, we may however encounter multicollinearity problems, if at the same time also year dummies are included into the regression to control for macroeconomic effects.[23] We therefore opt for a more parsimonious specification, allowing for three different effects: an anticipation effect, an effect in the first year of protection and an effect thereafter. However, results once more lead us to the conclusion that there is no significant impact of AD measures in any of these three periods considered.

Finally, we might worry that the standard errors reported in the regressions for the matched control group do not accurately depict true standard errors. More specifically, we are likely to underestimate the true standard errors, since calculated standard errors do not take into account the uncertainty that is generated by the fact that we match on the estimated and not on the true propensity score (Blundell and Costa Dias, 2009). A solution could be bootstrapping which, however, would cause inconsistency problems for nearest neighbour matching (Abadie and Imbens, 2008). In our case, an underestimation of standard errors is less of an issue. If true standard erros are larger, coefficients become less significant, which in turn strengthens the result that there is indeed no significant impact of AD measures on markups.

4.4 Discussion of results: why is there no impact?

There may be several reasons as to why there is no positive impact of trade protection on markups — a result that is in line with the findings of Blonigen et al. (2007) for the steel industry in the US. A first explanation could be related to import diversion. The existing evidence on import diversion for India, however, suggests that the impact of AD on imports from countries that are not named in AD cases is rather limited and that AD measures are effective in reducing overall imports. However, import diversion may still be a relevant explanatory factor, given that existing studies either consider relatively early periods of Indian AD policy only (Ganguli, 2008; Aggarwal, 2010) or narrowly defined sectors (Malhotra and Malhotra, 2008).

Second, there could be entry of new domestic firms into the market. Even though we cannot provide direct evidence on domestic market entry due to the lack of information on firm entry and exit in our firm-level data, this explanation does not seem to be relevant in the case of India. Indian AD policy is primarily applied in industries such as chemicals or basic metals (see Table 4), which are capital-intensive industries, and capital intensity has been shown to be one of the main barriers to market entry (Karakaya, 2002). The fact that firms' that file for protection have on average significantly higher markups is in line with this argument (see Table 7).

[23]Some of the preliminary results that were shown in a first draft of this paper were largely dependent on the inclusion of year dummies into the regression, which hinted us at this problem. The problem was exacerbated by the fact that we initially ran single-difference rather than difference-in-difference regressions.

Another possibility would be tariff jumping in the form of foreign direct investment (FDI). The idea that a foreign firm can "jump" AD measures by setting up a plant and engaging in FDI has been brought forward theoretically by Belderbos et al. (2004), in line with empirical evidence by for the US (Blonigen, 2002) and the United Kingdom (Girma et al., 2002). Again, since data are not available to us, we cannot directly provide any evidence on greenfield or brownfield FDI into the Indian market. However, barriers to FDI have been relatively high in India (Bajpai and Sachs, 2000), so that it is at least questionable whether foreign firms are willing to pay these fixed costs in order to jump a trade barrier that is in principle only temporary.

A further potential explanation is related to the fact that India imposes almost all of its AD measures on intermediate inputs. Input-using firms that are affected by AD on their input-side have the option to switch towards production activities that are less intensive in the input on which an AD tariff is levied. The import reduction due to AD measures is then not directly translated into an equally-sized increase in the market share for domestic producers. This is indeed what is found for the case of India and might prevent domestic producers' market power from rising (Vandenbussche and Viegelahn, 2014).

4.5 Digging deeper: evidence on unit values

The question can be raised whether the absence of any effect on the PCM at the firm-level possibly masks effects at the firm-product level. We already used firm-product level data on sales to identify protected firms. Now we are using these data to calculate unit values of products sold. In order to gain insights into the price dynamics at the firm-product level, we run different types of difference-in-difference regressions, accounting for firm-product-level and time fixed effects. Results are shown in Table 17.

First of all, we examine how unit values of protected goods' sales evolve when compared to the unit values of products sold by matched control firms, as idenfied through the nearest neighbour propensity score matching procedure (columns 1-2). We do not find any significant impact of AD measures. Next, we compare unit values of all other (non-protected) goods' sales of protected firms to the unit values of products sold by matched control firms (columns 3-4). Here we find that unit values of non-protected goods' sales of protected firms tend to evolve more favourably than unit values of products sold by control firms.

We finally run a regression, in which we directly compare unit values of protected and non-protected goods' sales within protected firms (columns 5-6), and find a significant impact. After AD tariffs are levied, prices of protected goods do not rise as fast as prices of non-protected goods, as indicated by the significant point estimate. This evolution of protected goods' prices is, however, not significantly different from the evolution of prices of products sold by control firms.

[Table 17]

These results clearly underline that domestic producers cannot benefit from protection through higher prices of the good for which AD protection is imposed. In contrast, results suggest that they tend to charge rather lower prices for the product that is protected from foreign competition than for other products, after AD measures are put in place. These results are in line with the absence of a market power effect and support this paper's main finding.

5 Conclusion

This paper uses a rich firm-level dataset to analyse the effects of antidumping protection on markups of protected firms in India, the country that is currently the most frequent user of antidumping policy. Using nearest neighbour matching techniques in combination with difference-in-difference regressions, we do not find any increase in domestic producers' profitability due to antidumping protection. This result is robust to a variety of specifications, estimation methods and methods to identify protected firms. We also do not find any impact of antidumping protection on the unit values of domestic producers' sales of the protected good. In fact, Indian producers tend to increase prices of protected goods less than prices of other goods.

Recent findings on input switching and antidumping policy (Vandenbussche and Viegelahn, 2014) provide a potential explanation for the absence of an impact on domestic producers' market power. Indian antidumping policy is primarily applied on intermediates that serve as inputs into production. When facing antidumping protection on their input side, input users tend to switch inputs, which possibly suppresses a potential increase of domestic producers' market power and might contribute to the findings of this paper.

Whether these results are good news for policy makers depends on their objective function. When imposing antidumping measures, the Indian government claims to aim at *providing expeditious relief to our domestic industry against the trade-distorting phenomenon of dumping.*[24] Indian antidumping law does not contain any clause that prescribes that antidumping measures should be overall welfare-improving.[25] This paper shows that relief does not come through the channel of increased price-cost margins. Domestic producers

[24]See foreword in *Antidumping - A Guide*, downloaded from the webpage of the Ministry of Commerce http://commerce.nic.in/traderemedies/Anti_Dum.pdf [2 August 2014].

[25]European antidumping law, for example, contains a *Community Interest Clause*. Relief from injury caused by dumping is denied, if it is not considered to be in the overall interest of the Community.

are on average not able to charge higher markups when antidumping measures are in force. If antidumping measures are exclusively meant to be an instrument to foster domestic producers' performance, these results question the effectiveness of this policy.

On the other side, these findings can be interpreted as good news for consumers and importers. Domestic producers that file for protection on average tend to charge already relatively high markups before protection comes into force. Import protection through antidumping measures does not seem to have any anti-competitive effect that would contribute to a further increase in markups. However, at the same time, these results do not imply that antidumping policy does not have any impact on consumers and importers. There are other channels through which antidumping policy may affect consumers and importers. Antidumping policy, for example, restricts the access to imported varieties of final goods and inputs, which may have a negative impact. In any case, more research is needed to better understand the motives of domestic producers to apply for trade protection, given that these firms on average cannot benefit through higher price-cost margins.

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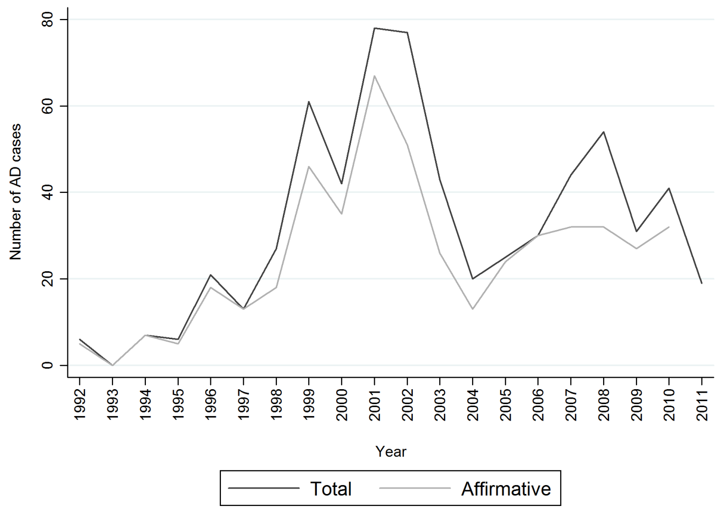
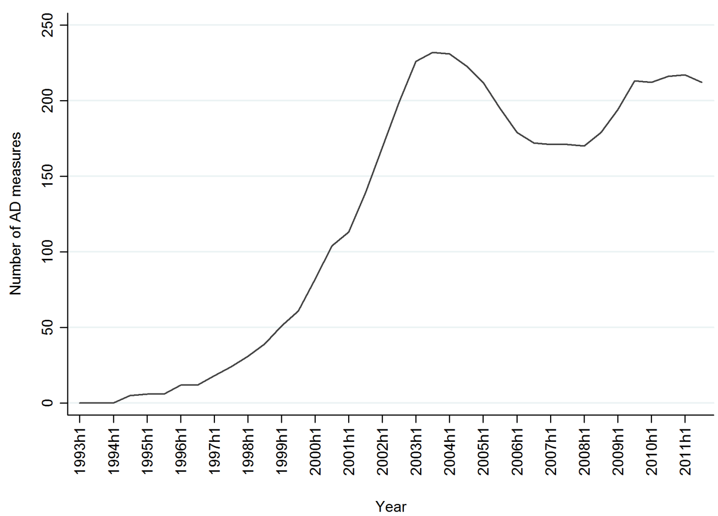
Figures

Figure 1: Number of Indian antidumping cases, by year



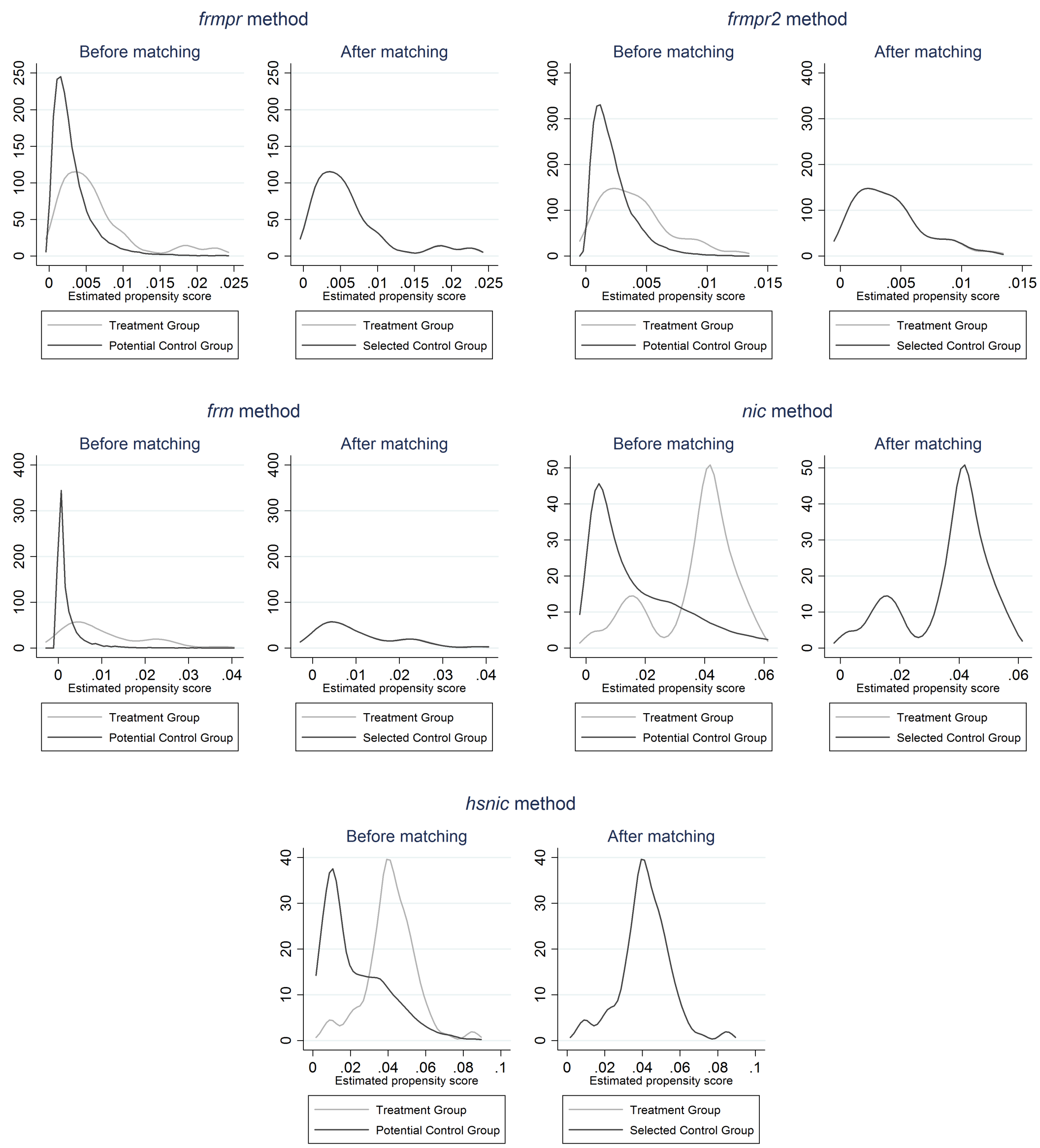
Source: Authors' calculations based on Bown (2012) and *Gazette of India*.

Figure 2: Number of Indian antidumping measures in force



Source: Authors' calculations based on Bown (2012) and *Gazette of India*.

Figure 3: Kernel density estimates of the propensity score, different methods



Notes: Potential control group includes all firm-year observations of firms never involved in AD cases. Treatment group includes all firm-year observations of protected firms in the year in which they initiated the AD case. Propensity score estimates are based on the probit model specified in equation 2. *frmpr*, *frmpr2*, *frm*, *nic* and *hsnic* refer to different methods that are used to identify protected firms (producers) in the firm-level dataset, as described in section 2.

Tables

Table 1: Descriptive statistics of firm-level data, 1999-2007

Variable	Mean	Std. Dev.	Min.	Max.	Average # obs. per year
Sales of goods	251.76	2859.29	0.01	203577.30	3535
Salaries and wages	10.35	60.25	0.01	3348.81	3292
Raw material expenses	124.20	1249.35	0.01	88016.99	3529
Power and fuel expenses	11.41	66.88	0.01	2997.83	3539
Net fixed assets	109.49	934.38	0.01	71188.59	3630
Market share (NIC 2-digit level)	0.01	0.02	0.00	0.45	3535
Market share (NIC 4-digit level)	0.03	0.09	0.00	1.00	3431
PCM	0.29	0.17	-0.35	0.63	2992
PCM (Difference)	-0.00	0.11	-0.89	0.94	2335

Source: Authors' calculations based on Prowess.
Notes: The table shows descriptive statistics of firm-level data. *Sales of goods*, *Salaries and wages*, *Raw material expenses*, *Power and fuel expenses* and *Net fixed assets* are reported in 10 Mio. Rupees. *Market share (NIC 2-digit)* (*Market share (NIC 4-digit)*) is calculated as the share of goods sales in the sum of all firms' goods sales in a 2-digit (4-digit) NIC industry, aggregated from firm-level data. *PCM* is calculated as specified below in equation 1. *PCM (Difference)* refers to the annual difference of PCM. Statistics are reported after data cleaning.

Table 2: Antidumping cases and their outcomes by initiation year, 1992-2011

	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002
Aff. Finding, AD	5	0	7	5	18	13	18	46	35	67	51
Aff. Finding, No AD	0	0	0	0	3	0	2	4	1	0	0
Neg. Finding, No AD	1	0	0	0	0	0	6	11	6	4	25
Under investigation	0	0	0	0	0	0	0	0	0	0	0
Withdrawn, No AD	0	0	0	1	0	0	1	0	0	7	1
Total	6	0	7	6	21	13	27	61	42	78	77

	2003	2004	2005	2006	2007	2008	2009	2010	2011	Total	Perc
Aff. Finding, AD	26	13	24	30	32	32	27	32	10	491	76.1
Aff. Finding, No AD	0	0	0	0	0	0	2	0	0	12	1.9
Neg. Finding, No AD	14	5	1	0	1	3	2	3	1	83	12.9
Under investigation	0	0	0	0	0	0	0	0	8	8	1.2
Withdrawn, No AD	3	2	0	0	11	19	0	6	0	51	7.9
Total	43	20	25	30	44	54	31	41	19	645	100

Source: Authors' calculations based on Bown (2012) and *Gazette of India*.

Table 3: Number of antidumping initiations, 1992-2011, by target country

Target Country	Number of Initiations
China	146
European Union	49
South Korea	48
Taiwan (China)	47
Thailand	35
USA	34
Japan	33
Indonesia	26
Singapore	23
Malaysia	20
Others	184

Source: Authors' calculations based on Bown (2012) and *Gazette of India*.

Table 4: Number of antidumping initiations, 1992-2011, by sector

Sector (NIC code 2 digit)	Number of initiations
Food products and beverages (15)	9
Textiles (17)	22
Paper and paper products (21)	13
Publishing, printing and re-production of recorded media (22)	7
Coke, refined petroleum products and nuclear fuel (23)	2
Chemicals and chemical products (24)	406
Rubber and plastic products (25)	19
Other non-metallic mineral products (26)	19
Basic metals (27)	88
Fabricated metal products, except machinery and equipments (28)	3
Machinery and equipment (29)	23
Electrical machinery and apparatus (31)	19
Radio, television and communication equipment and apparatus (32)	9
Medical, precision and optical instruments, watches and clocks (33)	5
Motor vehicles, trailers and semi-trailers (34)	3

Source: Authors' calculations based on Bown (2012) and *Gazette of India*. HS codes of each case were matched to one or in few cases to several NIC codes using the procedure described in footnote 13.

Table 5: Firms that are mentioned in the antidumping notifications

Multiple counting of firms	
Number of all firms mentioned in AD notifications	737
Production share that they at least account for on average	0.77
Number of firms identified in Prowess	579
By status:	
Petitioners	345
Supporters	195
Other firms	192
Status unknown	5
Single counting of firms	
Number of all different firms mentioned in AD notifications	425
Number of firms identified in Prowess	291

Source: Authors' calculations based on Prowess database, Bown (2012) and *Gazette of India*.

Table 6: Descriptive statistics of industry-level data

Variable	Mean	Std. Dev.	Min.	Max.	Average # obs. per year
Import penetration	0.40	0.32	0.00	1.00	107
Real import value growth	0.27	1.02	-0.99	27.74	107
MFN tariff change, 1996-2000	-6.09	10.42	-59.06	19.25	107
MFN tariff change, annual	-2.22	4.24	-25.44	49.00	47
MFN tariff	26.50	18.44	0.00	190.56	71
Herfindahl index	0.24	0.19	0.01	1.00	105

Source: UN Comtrade, *Prowess*, *Integrated Data Base* (IDB) of the WTO.
Notes: The table shows descriptive statistics of industry-level data with industries defined according to NIC 4-digit. *Import penetration* is calculated as import value as a share of the sum of goods sales value (net of good exports value) and import value. *Real import value growth* refers to the annual growth rate of imports, deflated with a sector-specific wholesale price index. *MFN tariff change, 1996-2000* refers to the average difference between the applied MFN tariff in force 2000 and the one in force 1996. *MFN tariff change, annual* refers to the average annual MFN tariff change. *MFN tariff* refers to the average reported MFN tariff in an industry. *Herfindahl index* refers to the Herfindahl index, calculated on the basis of firm-level data on goods sales.

Table 7: Results of probit regression

Dependent variable: First time initiation (yes/no)

	frmpr	*frmpr2*	*frm*	*nic*	*hsnic*
	(1)	(2)	(3)	(4)	(5)
Real import value growth (lagged)	-0.631***	-0.206	-0.006	-0.321***	-0.096***
	(0.171)	(0.161)	(0.020)	(0.053)	(0.034)
Import penetration (lagged)	0.236	0.472**	0.466**	-1.347***	-0.990***
	(0.184)	(0.195)	(0.226)	(0.158)	(0.155)
MFN tariff change 1996-2000	-0.004	-0.006	-0.015***	-0.021***	-0.022***
	(0.005)	(0.006)	(0.005)	(0.003)	(0.002)
Real net fixed assets (log, lagged)	0.102***	0.098***	0.271***	0.013	-0.013
	(0.025)	(0.029)	(0.032)	(0.016)	(0.014)
PCM (lagged)	0.374	0.642*	0.841**	0.640***	0.816***
	(0.316)	(0.377)	(0.376)	(0.192)	(0.159)
PCM (difference, lagged)	-0.666	-0.853*	-0.852	-0.844**	-0.639**
	(0.446)	(0.440)	(0.680)	(0.330)	(0.269)
GDP growth	-0.033	-0.019	-0.066**	0.057***	-0.017
	(0.021)	(0.024)	(0.026)	(0.019)	(0.013)
Constant	Yes	Yes	Yes	Yes	Yes
Number of observations	16348	16725	16862	10295	9895

Notes: ***, ** and * indicate a significance level of 1, 5 and 10 per cent, respectively. Reported are coefficients with cluster robust standard errors in brackets. *frmpr*, *frmpr2*, *frm*, *nic* and *hsnic* refer to different methods that are used to identify protected firms (producers) in the firm-level dataset, as described in section 2.

Table 8: **Matching results and test for balancing property**

	Protected firms	Potential control firms		Selected control firms	
	Mean	Mean	p-value	Mean	p-Value
***frmpr* method** / Number of obs.	53	15993		53	
Real import value growth (lagged)	0.03	0.31	0.00	0.06	0.63
Import penetration (lagged)	0.25	0.27	0.59	0.22	0.58
MFN tariff change 1996-2000	-4.87	-5.34	0.79	-7.04	0.32
Real net fixed assets (log, lagged)	3.41	2.51	0.00	3.59	0.51
PCM (lagged)	0.32	0.29	0.18	0.31	0.76
PCM difference (lagged)	-0.02	-0.00	0.35	-0.02	0.91
GDP growth	7.10	7.82	0.02	7.10	1.00
Propensity score	0.01	0.00	0.00	0.01	0.99
***frmpr2* method** / Number of obs.	39	16443		39	
Real import value growth (lagged)	0.17	0.32	0.00	0.26	0.14
Import penetration (lagged)	0.32	0.27	0.14	0.35	0.72
MFN tariff change 1996-2000	-6.83	-5.21	0.28	-6.91	0.97
Real net fixed assets (log, lagged)	3.43	2.54	0.00	3.32	0.78
PCM (lagged)	0.34	0.29	0.03	0.34	0.94
PCM difference (lagged)	-0.02	-0.00	0.11	-0.05	0.31
GDP growth	7.54	7.83	0.37	7.54	1.00
Propensity score	0.00	0.00	0.00	0.00	0.99
***frm* method** / Number of obs.	37	16598		37	
Real import value growth (lagged)	0.26	0.32	0.27	0.16	0.12
Import penetration (lagged)	0.25	0.27	0.68	0.29	0.50
MFN tariff change 1996-2000	-8.70	-5.13	0.00	-10.49	0.21
Real net fixed assets (log, lagged)	4.73	2.50	0.00	4.61	0.71
PCM (lagged)	0.38	0.29	0.00	0.35	0.47
PCM difference (lagged)	-0.01	-0.00	0.61	-0.03	0.61
GDP growth	7.11	7.83	0.08	7.11	1.00
Propensity score	0.01	0.00	0.00	0.01	0.98

(continued)

	Protected firms	Potential control firms		Selected control firms	
	Mean	Mean	p-value	Mean	p-Value
***nic* method** / Number of obs.	219	8374		219	
Real import value growth (lagged)	0.16	0.24	0.00	0.16	0.99
Import penetration (lagged)	0.15	0.32	0.00	0.12	0.04
MFN tariff change 1996-2000	-9.43	-5.51	0.00	-7.86	0.00
Real net fixed assets (log, lagged)	2.80	2.36	0.00	3.01	0.22
PCM (lagged)	0.35	0.29	0.00	0.35	0.92
PCM difference (lagged)	-0.02	-0.00	0.05	-0.01	0.63
GDP growth	8.22	7.84	0.01	8.27	0.80
Propensity score	0.04	0.02	0.00	0.04	1.00
***hsnic* method** / Number of obs.	300	6487		300	
Real import value growth (lagged)	0.22	0.52	0.00	0.19	0.39
Import penetration (lagged)	0.16	0.30	0.00	0.13	0.01
MFN tariff change 1996-2000	-12.03	-4.86	0.00	-9.15	0.00
Real net fixed assets (log, lagged)	2.81	2.46	0.00	2.69	0.38
PCM (lagged)	0.33	0.28	0.00	0.35	0.12
PCM difference (lagged)	-0.01	-0.00	0.39	-0.03	0.03
GDP growth	7.56	7.85	0.04	7.50	0.75
Propensity score	0.04	0.02	0.00	0.04	1.00

Notes: *Protected firms* and *Selected control firms* columns include firm-year observations that belong to different firms. *Potential control firms* column includes the whole panel of firm-year observations for the potential control group. p-value of t-test refers to the p-value of a two-sided t-test on mean equality between protected firms on the one hand and potential/selected control firms on the other hand. *frmpr*, *frmpr2*, *frm*, *nic* and *hsnic* refer to different methods that are used to identify protected firms (producers) in the firm-level dataset, as described in section 2.

Table 9: Difference-in-difference regressions, termination control group, panel FE IV regressions

Dependent variable: PCM					
	frmpr	*frmpr2*	*frm*	*nic*	*hsnic*
	(1)	(2)	(3)	(4)	(5)
AD x TR	-0.046**	-0.035	-0.035	-0.019	-0.028**
	(0.020)	(0.023)	(0.029)	(0.015)	(0.014)
AD	0.035*	0.027	0.038	0.000	0.019
	(0.020)	(0.022)	(0.029)	(0.014)	(0.012)
Capital-sales ratio	-0.062***	-0.087**	-0.032**	-0.004	-0.041*
	(0.013)	(0.044)	(0.015)	(0.003)	(0.022)
Market share	-0.176	-0.338	-0.931	0.266	-0.173
	(0.365)	(0.349)	(0.586)	(0.370)	(0.368)
Year FE	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes
R2	0.26	0.13	0.20	0.10	0.06
Hansen's J test p-value	0.21	0.29	0.42	0.85	0.86
Number of firms	115	98	67	420	761
Number of observations	685	599	443	2354	4117

Notes: ***, ** and * indicate a significance level of 1, 5 and 10 per cent, respectively. Reported standard errors in brackets are cluster robust. *Capital-sales ratio* and *Market share* are instrumented with their lagged values at t-1 and t-2. *frmpr*, *frmpr2*, *frm*, *nic* and *hsnic* refer to different methods that are used to identify protected firms (producers) in the firm-level dataset, as described in section 2.

Table 10: Difference-in-difference regressions, matched control group, panel FE IV regressions

Dependent variable: PCM

	frmpr	*frmpr2*	*frm*	*nic*	*hsnic*
	(1)	(2)	(3)	(4)	(5)
AD x TR	-0.024	0.019	-0.029	-0.012	-0.010
	(0.020)	(0.024)	(0.024)	(0.013)	(0.013)
AD	0.006	-0.050*	0.015	-0.008	0.001
	(0.018)	(0.026)	(0.018)	(0.009)	(0.016)
Capital-sales ratio	-0.061*	-0.029***	-0.068	-0.068***	-0.071***
	(0.035)	(0.005)	(0.091)	(0.023)	(0.016)
Market share	0.071	-0.264	-0.373	1.095**	0.095
	(0.354)	(0.206)	(0.519)	(0.488)	(0.177)
Year FE	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes
R2	0.16	0.07	0.10	0.04	.
Hansen's J test p-value	0.16	0.03	0.71	0.20	0.78
Number of firms	103	75	73	407	557
Number of observations	659	499	503	2483	3323

Notes: ***, ** and * indicate a significance level of 1, 5 and 10 per cent, respectively. Reported standard errors in brackets are cluster robust. *Capital-sales ratio* and *Market share* are instrumented with their lagged values at t-1 and t-2. *frmpr*, *frmpr2*, *frm*, *nic* and *hsnic* refer to different methods that are used to identify protected firms (producers) in the firm-level dataset, as described in section 2.

Table 11: Difference-in-difference regressions, matched control group, panel FE IV regressions, controlling for industry concentration

Dependent variable: PCM

	frmpr (1)	*frmpr2* (2)	*frm* (3)	*frmpr* (4)	*frmpr2* (5)	*frm* (6)
AD x TR	-0.026	-0.001	-0.022	-0.025	0.001	-0.028
	(0.020)	(0.020)	(0.023)	(0.020)	(0.020)	(0.025)
AD	0.007	-0.033	0.013	0.006	-0.035	0.013
	(0.018)	(0.024)	(0.017)	(0.018)	(0.024)	(0.018)
Capital-sales ratio	-0.059*	-0.030***	-0.060	-0.056	-0.031***	-0.070
	(0.035)	(0.005)	(0.091)	(0.037)	(0.005)	(0.093)
Market share				0.119	0.238	-0.610
				(0.327)	(0.164)	(0.652)
Herfindahl index	-0.011	-0.307***	0.015	-0.041	-0.316***	0.393
	(0.136)	(0.117)	(0.194)	(0.149)	(0.117)	(0.424)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
R2	0.16	0.09	0.16	0.17	0.09	0.07
Hansen's J test p-value	0.12	0.98	0.36	0.09	0.74	0.71
Number of firms	103	73	73	103	73	73
Number of observations	653	479	503	653	479	503

Notes: ***, ** and * indicate a significance level of 1, 5 and 10 per cent, respectively. Reported standard errors in brackets are cluster robust. In columns 1-3, the *capital-sales ratio* is instrumented with its lagged values at t-1 and t-2. In columns 4-6, the *capital-sales ratio* and the *market share* are instrumented with their lagged values at t-1 and t-2. *frmpr*, *frmpr2* and *frm* refer to different methods that are used to identify protected firms (producers) in the firm-level dataset, as described in section 2.

Table 12: Difference-in-difference regressions, matched control group, panel FE IV regressions, controlling for the applied MFN tariff

Dependent variable: PCM

	frmpr	*frmpr2*	*frm*	*frmpr*	*frmpr2*	*frm*
	(1)	(2)	(3)	(4)	(5)	(6)
AD x TR	-0.022	0.036	-0.026	-0.022	0.025	-0.025
	(0.024)	(0.026)	(0.027)	(0.019)	(0.025)	(0.024)
AD	0.021	-0.024	0.032	0.001	-0.053**	0.015
	(0.024)	(0.020)	(0.023)	(0.017)	(0.027)	(0.018)
Capital-sales ratio	-0.050**	-0.035***	0.022	-0.059	-0.029***	-0.062
	(0.022)	(0.003)	(0.035)	(0.037)	(0.005)	(0.086)
Market share	0.162	-0.161	-0.448	0.085	-0.268	-0.515
	(0.390)	(0.158)	(0.610)	(0.367)	(0.195)	(0.485)
Applied MFN tariff (actual data)	0.002	0.003*	0.000			
	(0.001)	(0.002)	(0.002)			
Applied MFN tariff (imputed)				0.002*	0.003*	0.002
				(0.001)	(0.002)	(0.002)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
R2	0.16	.	.	0.17	0.08	0.10
Hansen's J test p-value	0.26	0.38	0.39	0.16	0.06	0.68
Number of firms	96	69	70	102	73	72
Number of observations	469	346	360	651	484	495

Notes: ***, ** and * indicate a significance level of 1, 5 and 10 per cent, respectively. Reported standard errors in brackets are cluster robust. *Capital-sales ratio* and *Market share* are instrumented with their lagged values at t-1 and t-2. *frmpr*, *frmpr2* and *frm* refer to different methods that are used to identify protected firms (producers) in the firm-level dataset, as described in section 2.

Table 13: Difference-in-difference regressions, matched control group, panel FE IV regressions, effect in low growth vs. high growth periods

Dependent variable: PCM

	frmpr	*frmpr2*	*frm*	*nic*	*hsnic*
	(1)	(2)	(3)	(4)	(5)
AD x TR x Low growth dummy	0.038	0.048	0.004	-0.007	-0.036
	(0.026)	(0.032)	(0.031)	(0.025)	(0.026)
AD x TR	-0.031	0.012	-0.031	-0.010	-0.001
	(0.021)	(0.023)	(0.028)	(0.014)	(0.012)
AD x Low growth dummy	0.004	-0.016	-0.043	-0.011	0.031
	(0.027)	(0.033)	(0.028)	(0.012)	(0.026)
AD	-0.005	-0.049*	0.038	-0.003	-0.009
	(0.028)	(0.028)	(0.024)	(0.011)	(0.010)
Capital-sales ratio	-0.060*	-0.029***	-0.070	-0.068***	-0.071***
	(0.035)	(0.005)	(0.095)	(0.022)	(0.016)
Market share	0.047	-0.279	-0.383	1.076**	0.092
	(0.361)	(0.227)	(0.528)	(0.482)	(0.178)
Year FE	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes
R2	0.17	0.07	0.10	0.04	.
Hansen's J test p-value	0.18	0.03	0.71	0.20	0.78
Number of firms	103	75	73	407	557
Number of observations	659	499	503	2483	3323

Notes: ***, ** and * indicate a significance level of 1, 5 and 10 per cent, respectively. Reported standard errors in brackets are cluster robust. *Capital-sales ratio* and *Market share* are instrumented with their lagged values at t-1 and t-2. *frmpr*, *frmpr2*, *frm*, *nic* and *hsnic* refer to different methods that are used to identify protected firms (producers) in the firm-level dataset, as described in section 2.

Table 14: Difference-in-difference regressions, matched control group, Arellano-Bond regressions

Dependent variable: PCM

	frmpr	*frmpr2*	*frm*	*nic*	*hsnic*
	(1)	(2)	(3)	(4)	(5)
AD x TR	0.013	0.033	-0.002	-0.009	-0.019*
	(0.031)	(0.028)	(0.020)	(0.014)	(0.011)
AD	-0.006	-0.032	0.001	-0.004	-0.003
	(0.019)	(0.025)	(0.018)	(0.010)	(0.010)
PCM (lagged)	0.438***	0.364**	-0.076	0.277***	0.203***
	(0.121)	(0.149)	(0.217)	(0.091)	(0.069)
Capital-sales ratio	0.032	-0.044***	-0.028*	-0.030**	-0.004
	(0.064)	(0.008)	(0.015)	(0.013)	(0.004)
Market share	0.865	0.221	0.426	-0.320	-0.242
	(0.986)	(0.282)	(0.337)	(0.409)	(0.357)
Year FE	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes
Wald Chi2 Test p-value	0.00	0.00	0.00	0.00	0.00
2nd order serial corr test p-value	0.91	0.42	0.40	0.24	0.16
Hansen's J test p-value	0.92	0.64	0.49	0.41	0.16
Number of firms	102	77	71	411	543
Number of observations	489	379	367	1878	2506

Notes: ***, ** and * indicate a significance level of 1, 5 and 10 per cent, respectively. Reported standard errors in brackets are cluster robust. Instruments include the moment restrictions on *PCM*, the *Capital-sales ratio* and the *Market share* at t-2. *frmpr*, *frmpr2* and *frm*, *nic* refer to different methods that are used to identify protected firms (producers) in the firm-level dataset, as described in section 2.

Table 15: Difference-in-difference regressions, matched control group (alternative matching procedures), Arellano-Bond regressions

Dependent variable: PCM						
	3 nearest neighbours			Within-industry		
	frmpr	*frmpr2*	*frm*	*frmpr*	*frmpr2*	*frm*
	(1)	(2)	(3)	(4)	(5)	(6)
AD x TR	0.012	0.012	-0.002	0.005	0.019	0.004
	(0.027)	(0.020)	(0.018)	(0.032)	(0.023)	(0.023)
AD	-0.011	-0.017	0.003	-0.004	-0.023	-0.004
	(0.012)	(0.014)	(0.014)	(0.021)	(0.020)	(0.022)
PCM (lagged)	0.421***	0.419***	0.180	0.446***	0.486***	-0.151
	(0.110)	(0.115)	(0.116)	(0.127)	(0.160)	(0.270)
Capital-sales ratio	-0.058*	-0.041***	-0.042***	-0.045	-0.041***	0.013
	(0.030)	(0.005)	(0.011)	(0.046)	(0.014)	(0.033)
Market share	0.309	0.261	-0.169	0.464	-0.261	1.472
	(0.338)	(0.315)	(0.296)	(0.649)	(0.728)	(1.496)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Wald Chi2 Test p-value	0.00	0.00	0.00	0.00	0.00	0.00
2nd order serial corr test p-value	0.28	0.50	0.69	0.54	0.40	0.89
Hansen's J test p-value	0.73	0.38	0.55	0.49	0.95	0.28
Number of firms	203	153	141	103	74	69
Number of observations	977	762	698	484	381	339

Notes: ***, ** and * indicate a significance level of 1, 5 and 10 per cent, respectively. Reported standard errors in brackets are cluster robust. Instruments include the moment restrictions on *PCM*, the *Capital-sales ratio* and the *Market share* at t-2. *frmpr*, *frmpr2*, *frm*, *nic* and *hsnic* refer to different methods that are used to identify protected firms (producers) in the firm-level dataset, as described in section 2.

Table 16: Difference-in-difference regressions, matched control group, further robustness checks

Dependent variable: PCM						
	Panel FE IV regressions: Alternative PCM definition			Panel FE regressions: Only year dummies		
	frmpr	*frmpr2*	*frm*	*frmpr*	*frmpr2*	*frm*
	(1)	(2)	(3)	(4)	(5)	(6)
AD x TR	0.015	-0.015	-0.004	-0.028	-0.012	-0.018
	(0.018)	(0.015)	(0.017)	(0.022)	(0.022)	(0.019)
AD	0.005	-0.001	0.002	-0.001	-0.035	0.010
	(0.017)	(0.015)	(0.021)	(0.018)	(0.022)	(0.016)
Capital-sales ratio	-0.035	-0.000	0.041			
	(0.035)	(0.018)	(0.040)			
Market share	-0.304	0.167	-0.028			
	(0.302)	(0.109)	(0.249)			
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
R2	0.12	0.08	.	0.05	0.09	0.12
Hansen's J test p-value	0.44	0.09	0.52			
Number of firms	96	70	65	106	78	74
Number of observations	603	471	447	735	551	530

Notes: ***, ** and * indicate a significance level of 1, 5 and 10 per cent, respectively. Reported standard errors in brackets are cluster robust. In columns 1-3, the *capital-sales ratio* and the *market share* are instrumented with their lagged values at t-1 and t-2. *frmpr*, *frmpr2* and *frm* refer to different methods that are used to identify protected firms (producers) in the firm-level dataset, as described in section 2.

Table 17: Difference-in-difference regressions on product-level unit values of sales, matched control group, panel FE regressions

	Dependent variable: Unit values					
	AD products of treated firms vs. All products of control firms		Non-AD products of treated firms vs. All products of control firms		AD products of treated firms vs. Non-AD products of treated firms	
	frmpr	*frmpr2*	*frmpr*	*frmpr2*	*frmpr*	*frmpr2*
	(1)	(2)	(3)	(4)	(5)	(6)
AD x TR	0.057	-0.034	0.145**	0.059	-0.105**	-0.110*
	(0.044)	(0.046)	(0.061)	(0.075)	(0.051)	(0.056)
AD	-0.056*	0.005	-0.129***	-0.041	0.003	0.028
	(0.031)	(0.031)	(0.044)	(0.049)	(0.032)	(0.037)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
R2	0.077	0.15	0.12	0.12	0.15	0.12
Number of firm-products	149	109	209	157	256	195
Number of observations	841	677	1161	892	1267	1084

Notes: ***, ** and * indicate a significance level of 1, 5 and 10 per cent, respectively. Reported standard errors in brackets are cluster robust. *frmpr* and *frmpr2* refer to different methods that are used to identify protected firm-products in the firm-level dataset, as described in section 2.