TRADE POLICY AND PERFORMANCE:
PLANT-LEVEL EVIDENCE FROM MANUFACTURERS

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ABSTRACT

This dissertation examines the effect of changes in trade policies on the behavior and performance of manufacturing plants. Chapter 1 describes the effects of a temporary increase in tariffs on the performance and behavior of U.S. manufacturing plants. Using antidumping duties as an example of temporary protection, I compare the responses of protected manufacturers to those predicted by new models of trade with heterogeneous firms. I find that apparent increases in revenue-based productivity associated with temporary protection are primarily due to increases in prices and mark-ups. In fact, antidumping duties lower physical productivity among the set of protected plants reporting output data in units of quantity. Moreover, antidumping duties allow for the continued operation of low-productivity plants that likely would have otherwise ceased production. As a result, temporary protection slows the process of output rationalization, with less productive plants producing a greater share of total output, leading to a reduction in aggregate productivity growth. Importantly, plants that are denied protection by the government are no more likely to exit than protected plants. Rather, they adjust by

dropping the unprotected product and producing other, potentially higher-productivity products.

Chapter 2 identifies determinants of productivity growth among Colombian manufacturers during a period of unilateral trade liberalization. I find that lower tariff rates were associated with an expansion in the extensive margin of foreign input usage, as well as an increase in investment in new machinery. The expansion in extensive margin of foreign input use is found to be productivity-augmenting, in line with the predictions of Ethier (1982). Higher investment in new machinery had no effect on current productivity, although there is some evidence that these investments have a positive effect on future productivity. Industry concentration, plant scale and the intensity of foreign input usage—three other potential channels for productivity growth—were unaffected by trade liberalization.

Chapter 3 outlines an algorithm for concording ten-digit Harmonized System export and import codes over time, describes the concordances we construct for 1989 to 2004 and provides Stata code that can be used to construct similar concordances for arbitrary beginning and ending years from 1989 to 2007.

The research in Chapter 1 of this dissertation was conducted while the author was a Special Sworn Status researcher at the U.S. Census Bureau, Center for Economic Studies. Any opinions and conclusions expressed herein are those of the author(s) and do not necessarily represent the views of the U.S Census Bureau. All results have been reviewed to ensure that no confidential information is disclosed. Support for this research at the Washington RDC from NSF (ITR-0427889) is also gratefully acknowledged.

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TABLE OF CONTENTS

Chapter 1: Plant-Level Responses to Antidumping Duties: Evidence From U.S. Manufacturers

Section 1: Introduction

What are the effects of temporary tariff protection on U.S. manufacturers? This question has become increasingly important as antidumping duties have become one of the primary forms of trade protection, in the U.S. and world-wide. Moreover, the answers to this question have implications that reach beyond antidumping policy. Studying U.S. manufacturers' reactions to antidumping duties can also provide new insight into the heterogeneous responses of firms to changes in tariff rates, within the context of a major trade shock in a developed country. This paper provides the first micro-level evidence on the effects of antidumping duties in the United States, using a dataset that includes the full population of U.S. manufacturing establishments (plants). Furthermore, through the use of output data measured in units of quantity, I am able to detect substantial differences between the effects of antidumping duties on plants' physical and revenue productivities.

While antidumping duty rates can reach into the triple digits and drastically alter trade flows, there are disagreements about some of their most fundamental implications, including their effect on firm and plant-level productivity. On one hand, there is a substantial literature that suggests that any increase in tariffs should decrease productivity. In Melitz (2003), an increase in tariffs—or a failure to decrease tariffs—allows for the continued operation of low-productivity firms that would have otherwise exited, resulting in a decrease in mean firm-level productivity. In addition, Bernard, Redding and Schott (2006), describe a channel for within-plant productivity growth during trade liberalization, which arises when plants drop their least productive products and reallocate resources to their most productive products. Pavcnik (2002) and Fernandes (2007) (for developing countries) and Bernard, Jensen and Schott (2006) (for the U.S.) provide empirical evidence showing that productivity and nominal tariffs are negatively correlated.

In contrast, there is evidence that tariff protection—particularly temporary protection—can increase firm or plant-level productivity by increasing the incentive to invest in new technology. Matsuyama (1990) was among the first to show that temporary protection can speed up the time of technology adoption, while noting that the government's threat to remove protection if the domestic firm fails to invest is not credible. Similarly, Miyagiwa and Ohno (1995, 1999) show that protection can induce investment in a fixed cost technology by increasing the market share of domestic firms. These theoretical models are supported by empirical results in Konings and Vandenbussche (2008) showing that revenue-based productivity increased among E.U. manufacturers receiving temporary antidumping protection.[1] As noted in that paper, however, increases in revenue productivity can be caused not only by increases in physical productivity, but also by increases in prices and mark-ups.

I examine these issues by comparing the behavior of a treatment group of plants that received protection to three control groups of plants in similar industries that did not receive protection. As described below, these control groups are constructed in a manner that eliminates two potential sources of bias: a self-selection bias that exists if industries that apply for protection differ from those that do not apply and a "government-selection bias" that arises if the government bases its decision of whether to provide protection on variables that are correlated with productivity. I employ a difference-in-difference estimator to estimate the effect of antidumping protection, which nets out time-invariant differences between the treatment and control groups, as well as macro-level shocks affecting the treatment and control groups identically. In addition, I examine whether variation in the

[1] Konings and Vandenbussche (2008) find that antidumping duties were associated with increases in mean plant-level productivity. An important additional result is that antidumping duties allowed for technological catch-up by the least productive firms, while firms with high ex-ante productivities experienced productivity declines.

effective antidumping duty rate protecting plants leads to heterogeneous responses to protection.

I find that the effect of antidumping duties on plant-level productivity depends crucially on whether output is measured in revenue or physical units of quantity. While antidumping protection is associated with an increase in plant-level revenue productivity, these increases are driven primarily by increases in prices and mark-ups.[2] Antidumping duties actually lower physical productivity among the set of protected plants reporting output data in units of quantity. These results underscore the importance of differentiating between revenue and physical productivity—a distinction that has received relatively little attention in the field of international trade. In fact, this distinction is particularly important when considering the case of antidumping duties, since increases in prices and markups would likely be taking place at the same time as changes in physical productivity.

Antidumping duties also provide a useful way of examining some of the best-known results from the heterogeneous-firm literature. In particular, while most empirical research on the responses of firms to trade liberalization has focused on

[2] I examine the effect of antidumping duties on both prices and mark-ups, since mark-ups will be less responsive to antidumping protection if suppliers are able to extract rents from protected plants through higher prices.

developing countries, antidumping protection can provide an example of a major trade shock in a large, developed country—in this case, the United States. Moreover, in many heterogeneous-firm models, trade liberalization increases aggregate productivity as resources are shifted from less productive to more productive uses. By studying the imposition of antidumping duties, it is possible to examine whether some of these newly recognized benefits of trade liberalization are eliminated when protection is imposed.

One well-documented way that trade liberalization reallocates resources from low to high-productivity uses is through the exit of the least productive firms. In the theoretical literature, exit of low-productivity firms during trade liberalization is a key result of Melitz (2003), Bernard, Eaton, Jensen and Kortum (2003) and Bernard, Redding and Schott (2006). These theoretical results are also supported by robust empirical evidence. Pavcnik (2002) and Bernard, Jensen and Schott (2006) have shown that decreases in trade costs bring about the exit of low-productivity firms and plants, yielding substantial increases in aggregate productivity. To examine whether antidumping protection slows this process, I compare the probability of exit among a treatment group of plants that received antidumping protection to that in a control group of unprotected plants.

Bernard, Redding and Schott (BRS) (2006, 2008) identify an additional channel for resource reallocation and productivity growth during trade liberalization, through product-switching by multi-product firms. BRS (2006) provide models of firms with exporting and production, where overall firm productivity is a combination of firm and firm-product components. Trade liberalization yields productivity growth by forcing firms to drop marginally productive products and by forcing the least productive firms to exit.[3] But if antidumping protection allows low-productivity plants to continue producing low-productivity products, it will have negative effects on both plant-level and aggregate productivity. I examine the effect of antidumping duties on plants' product-switching activities by comparing the

[3] BRS (2006) provides a useful framework for examining how multi-product firms react to changes in trade policy. There are, however, *important* differences between the framework in BRS (2006) and the temporary antidumping protection examined in this paper. First, BRS (2006) is based explicitly on a multilateral trade liberalization occurring as two countries move from a closed economy to an open-economy equilibrium. In antidumping duty proceedings, changes in trade policy are unilateral and are targeted against imports from a particular country. Second, BRS (2006) focuses on trade liberalization for all products. Antidumping duty investigations, on the other hand, involve a single product or a set of closely related products. Third, the trade liberalization in BRS is permanent, while antidumping duties are temporary.

probability of dropping protected products in the treatment group to the probability of dropping products that did not receive protection in the control group.

I find that antidumping duties allow for continued production by low-productivity plants that would have otherwise stopped producing. Importantly, this effect manifests itself not through decreased plant-level exit, but rather through a reduction in product-switching among protected plants. Protected plants are no less likely to exit than those that did not receive protection. But while low-productivity plants that are turned down for antidumping duties by the government react by dropping products, protected plants are able to continue producing the same products. As a result, antidumping duties likely decrease the productivity gains that would otherwise occur as a result of product-switching.

By allowing for continued production by low-productivity plants, antidumping duties may eliminate the benefits of trade liberalization associated with output rationalization, where high-productivity plants increase their market share at the expense of low-productivity plants. I measure this effect by decomposing aggregate productivity into mean plant-level productivity and a term that measures the degree to which higher-productivity plants produce a larger share of output, as in Olley and Pakes (1996). I find that antidumping protection slows the process of output rationalization, decreasing aggregate productivity growth. While the degree of output rationalization is significantly higher among protected plants prior to receiving protection, the control group of unprotected plants steadily increases its level of output rationalization as the antidumping duties set in. By the end of the period of analysis, the control group has overtaken the treatment group, to exhibit a higher level of output rationalization.

The remainder of the paper is organized as follows. Section 2 describes the data. Section 3 provides a brief discussion of the antidumping investigation process in the United States, as well as a description of the products typically involved in antidumping investigations. Section 4 describes the empirical strategy and reports results. Section 5 concludes.

Section 2: Data

This analysis uses plant-level and plant-product-level[4] data from the U.S. Census Bureau's (Census) Longitudinal Research Database (LRD) for the years 1987 to 1997. Total factor productivity is calculated using data from the Census of Manufactures (CMF). The CMF contains plant-level data on output (value of shipments and sometimes quantity), as well as input data including the number of

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[4] Plant-product-level data refers to output data for every product produced at every plant. These shipment data are measured in revenue for all products and in units of physical quantity for a subset of products.

production and non-production employees, raw material usage, investment, depreciation and book value of capital. The CMF is conducted every five years, in years ending in two and seven (e.g. 1987, 1992, 1997) and all U.S. manufacturers, regardless of size, are required by law to respond.[5]

An important benefit of the CMF is the availability of output data measured in units of quantity for certain products. The availability of quantity-based output data allows for the calculation of physical productivity—in addition to the standard revenue productivity—as well as average unit prices and price-cost mark-ups. The ability to examine physical productivity, prices and mark-ups is extremely important when studying antidumping duties, since changes in physical productivity are likely accompanied by increases in prices and mark-ups. These quantity-based output data have been used in recent studies examining the differences between revenue and physical productivity, including Foster, Haltiwanger and Syverson (2008).

It is important to define a number of terms that will be used throughout this paper. The term plant refers to a manufacturing establishment, which is a production

[5] The CMF collects a limited set of data from small manufacturers, referred to in the data as "administrative records." Since input usage data may be imputed for administrative records, they have been excluded from the analysis. This exclusion of administrative records is standard in research employing the LRD. See, e.g. Bernard, Redding and Schott (2008).

facility located at a single physical location. Products and industries are 5-digit and 4-digit categories of the Standard Industrial Classification (SIC), respectively.[6] A product group is the set of plants producing a particular product. Lastly, an investigated product is a product that was involved in an antidumping investigation, regardless of the outcome of the investigation.

The use of plant-level data is an important innovation of this paper and provides many advantages over more aggregated data, even including firm-level data. Many firms involved in petitioning for antidumping protection are large multi-product manufacturers. In fact, some firms participated as petitioners in multiple antidumping investigations involving multiple products. Individual plants on the other hand, tend to produce a much narrower set of products than firms as a whole. The use of plant-level data, therefore allows for much more accurate matching between the products named in contingent protection investigations and the facilities that actually produce those products.

The benefits of plant-level matching can be seen clearly by examining the experience of a specific firm, the integrated steel-maker United States Steel. According to its 2006 annual report, U.S. Steel operated 24 plants in the United

[6] The 1987 SIC contains 459 four-digit industries and 1,848 five-digit products.

States, producing multiple products including flat-rolled sheets, tin mill, strip mill plate, galvanized sheets and tubular products.[7] Moreover, several of U.S. Steel's products have been subject to antidumping or countervailing duty protection over the years including Corrosion-Resistant Carbon Steel Flat Products (1993), Cut to Length Plate (1979, 2003), Seamless Pipe (1995), Oil-Country Tubular Goods (1995), Hot-Rolled Steel Products (2001) and Welded Large-Diameter Line Pipe (2001, 2002).[8] In the case of U.S. Steel, firm-level data are not sufficient for defining when or in what way the firm received protection. With plant-level data, however, I am able to identify the plants producing the specific products covered by antidumping duties applied in specific years.

In addition, I am able to greatly refine the identification of plants that did and did not receive contingent protection through the use of plant-product-level data contained in the LRD. These data report the full list of products manufactured at each plant, as well as the value, and sometimes quantity, of shipments attributable to each product. The availability of this plant-product-level data represents an

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[7] United States Steel at 32. Available online at:

http://www.uss.com/corp/investors/annual_reports/2006-annual-report.pdf

[8] United States Steel at 15-16. http://www.uss.com/corp/investors/annual_reports/2006-annual-report.pdf

additional level of disaggregation beyond the “major industry” codes generally used to identify plants and firms in micro-level datasets.

The list of products involved in antidumping investigations in the United States is from version 3.0 of Chad Bown’s Global Antidumping Database.[9] Products subject to antidumping investigations are identified using the Harmonized Tariff System (HTS) and products may be defined from the 4-digit level to the 10-digit level.[10] In addition to a description of the products involved in each investigation, the antidumping database provides the dates and outcomes of each phase of the investigation—e.g. preliminary and final injury and dumping determinations—along with the final remedy. The analysis in this paper considers the effects of antidumping investigations that were completed during the period from 1988 to 1996. This setup ensures that I am able to observe plant-level outcomes both before and after the imposition of protection for every product group.[11] Lastly, because

[9] Available online at http://people.brandeis.edu/~cbown/global_ad/.

[10] Although the HTS was not effective until 1989, investigations in Bown’s Global Antidumping Database that ended in 1988 were assigned HTS numbers, ex-post.

[11] Because products in antidumping investigations are classified under the HTS, while products in the LRD are classified under the SIC, it is necessary to concord the two product classification systems. The matching of HTS codes to SIC codes takes place through a set of SIC Base Codes (SICBase) developed by Census. SICBase codes are a bridge that connects the HTS—where products are defined solely based

successful antidumping investigations in the United States almost always result in ad-valorem tariffs—rather than price undertakings or suspension agreements—I am able to study the effect of variation in the antidumping duty rate on productivity.

Section 3: Antidumping Duties in the United States

Under GATT Article VI and the WTO's Antidumping Agreement, WTO members are permitted to impose discriminatory tariffs on goods sold by foreign producers at prices that are deemed to be less than fair value (LTFV), if these sales result in material injury to the domestic industry. In the United States, sales are considered to be made at LTFV—i.e. dumped—when a foreign firm sells a good in

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on their physical characteristics—to the SIC, where products are also classified based on their method of production. For this reason, Census assigns a single SICBase to each HTS10. This SICBase may contain a single SIC5 if the HTS10 is a subset of a single SIC5, or multiple SIC5s if the HTS10 fits several SIC5 categories. Using a three step process, I am then able to determine which plants produce products that were involved in antidumping investigations:

<u>Step 1</u>: SICBase codes are assigned to the HTS10 codes contained in the antidumping dataset (referred to here as BOWN_AD for brevity) using an HTS10-SICBase concordance (HTS_SICBase) published by the Census Bureau.

<u>Step 2</u>: SICBase codes are assigned to each SIC5 in the plant-product-level data in the LRD using a SIC5-SICBase concordance known as the Principle Differences file (PD). The 1992 principle differences file, which is used for the analysis in this paper can be found online at http://www.census.gov/epcd/www/intronet.html.

<u>Step 3</u>: The BOWN_AD antidumping dataset is merged to the LRD using the SICBase codes.

the United States at a price that is below that offered on comparable sales in its home market, or below its average total cost (ATC).[12]

Antidumping investigations in the United States are initiated by individual firms, trade associations or sometimes labor unions, which are referred to in antidumping investigations as petitioners. The foreign firms selling allegedly dumped merchandise are referred to as respondents. Petitioners apply for antidumping protection by submitting a petition to the Import Administration of the Department of Commerce (DOC) and the International Trade Commission (ITC). The DOC determines whether sales made by foreign firms in the U.S. are being made at LTFV. The ITC determines whether the U.S. industry has been injured as a result of the dumping.

If the DOC finds that sales have been made at LTFV and the ITC concludes that these sales have injured U.S. producers, an ad-valorem tariff is placed on

[12] There are additional subtleties to the LTFV determination. For market economies, the preferred price comparison is between sales by the foreign producer in the U.S. and its home market. If there are insufficient sales in the foreign producer's home market, U.S. prices are compared to sales in a third country. If there are insufficient sales in the third country, U.S. prices are compared to the "constructed value (CV)" of the foreign producer's merchandise, which is gathered from the firm's cost accounting system and is essentially ATC. Sales made by firms in non-market economies are always compared to the "normal value (NV)" the firm's merchandise, which is again essentially the firm's ATC.

imports of goods from the respondents' home countries. This ad-valorem tariff, which is known as an antidumping duty is equal to the percentage difference between the U.S. price and the home-market price or ATC. I refer to the magnitude of the antidumping duty as the antidumping duty rate. Because the antidumping duty is applied to all dumped goods, it benefits the petitioners, as well-as non-participating producers of the investigated product.

Table 1 reports the types of products involved in antidumping investigations from 1988 to 1996, showing the number of antidumping duty investigations by 2-digit HTS Chapter. The most frequent seekers of antidumping duties were producers of "Iron and Steel" (Chapter 72) and "Articles of Iron and Steel" (Chapter 73). Other active applicants for antidumping protection included producers of machinery and appliances (Chapters 84 and 85), inorganic and organic chemicals (Chapters 28 and 29) and transportation vehicles and parts (Chapter 87). As these examples indicate, antidumping duties are primarily used to protect relatively homogenous manufactured goods.

Table 2 shows the number of antidumping investigations completed, by outcome for the years 1980 to 2005. The number of antidumping investigations tends to increase during and immediately following periods of recession, and we see that this phenomenon did, in fact, occur following the recession of 1990-1991, when the number of new investigations spiked in 1991 and 1992. Aside from this countercyclical trend in new investigations, the period from 1988 to 1996 was typical in terms of the number of investigations initiated.

Section 4: Empirical Strategy and Results

Pre-Estimation Definitions

A. Definition of Treatment and Control Groups

To borrow terms from the program analysis literature, I conduct this analysis by comparing the behavior of plants in a treatment group receiving antidumping protection to plants in a control group that do not. The treatment group consists of plants producing products that applied for and received antidumping protection. Each plant in the treatment group is assigned a date of treatment and an ad-valorem duty rate,[13] which comes from the results of the antidumping investigation associated with the product it produces. If a plant produces more than one product that receives protection, the treatment date and duty are those associated with the product that accounts for the highest share of its output.

[13] Of the 160 antidumping investigations initiated between 1988 and 1996, 5 ended with suspension agreements. For these cases, no ad-valorem antidumping duty rate was available.

Comparing the behavior of these treated plants to a control group—rather than simply examining changes in treated plants over time—allows for netting out changes in plant-level variables that are independent of the treatment. Using the difference-in-difference framework described in more detail below I am also able to net out macro-level shocks that affect all manufacturers equally.

In the framework being examined in this paper, a natural concern is that any estimated treatment effects could be affected by a self-selection bias, because the set of plants that apply for antidumping protection are almost certainly different from those that do not. For example, antidumping applicants produce goods that are subject to import competition, perceive themselves as being injured by imports and operate in industries capable of cooperating to file a case.

To control for this self-selection bias, I use an approach employed in Konings and Vandenbussche (2008) to define a first control group. Specifically, I define the control group to be plants producing products that applied for antidumping duties, but were denied protection by the government. I will refer to this control group as the termination control group, hereafter. As with treated plants, plants in the termination control group produce products characterized by high import competition, perceive themselves as injured by imports and are able to organize the industry to file an antidumping petition. Moreover, as shown in Table 3, control plants are concentrated in the same sectors that successfully apply for protection—especially primary and fabricated metals, and industrial and electronic equipment.[14] In addition, as described in Table 4, plants in the treatment and control groups are comparable in terms of their total value of shipments, number of employees and capital to labor ratios. Importantly, they also display nearly identical mean levels of total factor productivity and labor productivity in the pre-treatment year of 1987.

Despite the similarity of the treatment and control groups, there is a possibility of an additional "government selection bias," if the government only grants protection to petitioners that meet certain criteria. In particular, the ITC considers variables such as employment and import penetration when deciding whether to provide protection in antidumping investigation. Because these variables are likely correlated with productivity, estimates based on the termination control group may be biased.

[14] Observations where the treatment and control groups overlap have been dropped from the analysis. Overlapping of treatment and control groups can occur for two reasons. First, a single SIC5 product could receive protection from one antidumping investigation but be denied protection in another. This is possible if the HTS10 products defined in two different antidumping investigations both map into the same SIC5. In addition, a single plant could produce two products, where one product receives protection and the other is turned down for protection.

I control for this potential government selection bias by constructing two alternative control groups composed of unprotected industries that are similar to protected industries in terms of the variables considered by the ITC in antidumping investigations. Specifically, these two alternative control groups, which I will refer to as the "matched control groups" are formed by estimating a probability of protection based on industry-level independent including lagged import penetration, lagged employment, GDP growth, labor productivity and price growth.[15] Each matched control group is composed of plants in industries with a high predicted probability of protection, but that did not actually receive protection.

The first matched control group—matched control group 1—is formed by estimating the probability of receiving antidumping protection for all industries. This means that every industry that did not receive protection has the potential to be included in matched control group 1, including industries that never applied for protection and those that applied, but were turned down by the government. Matched control group 1 is formed by estimating a multinomial logit model where the dependent variable takes a value of 1 if an industry never applied for protection,

[15] These variables have been used to explain the probability of receiving antidumping protection in Blonigen and Park (2004) and Konings and Vandenbussche (2008).

2 if it applied and was turned down and 3 if it applied for and received protection. Independent variables are the determinants of protection considered by the ITC and described above. Matched control group 1 is then the set of plants in industries that had a probability of protection greater than the 75th percentile of that in protected industries, but that did not receive protection.[16]

Matched control group 2 is formed by only considering industries that applied for protection. A logit model is estimated where the dependent variable equals 1 for industries that received protection and 0 for industries that applied for but did not receive protection. Independent variables are the same as those considered when constructing matched control group 1. The control group is composed of plants in industries did not receive protection but that were in the top 75th percentile in terms of their predicted probability of protection. Matched control group 2 has the attractive property of being composed of plants in industries that applied for protection—thus controlling for potential self-selection bias—while also being highly similar to the treated industries, in terms of the variables considered by the ITC.

[16] This is the same probability cutoff used to form a matched control group in Konings and Vandenbussche (2008).

Results of the multinomial logit and logit regressions used to create the two matched control groups are reported in Table A.1 of Appendix 1. Estimated coefficients take the expected sign and are consistent with results in Blonigen and Park (2004) and Konings and Vandenbussche (2008). Specifically, the probability of receiving antidumping protection increases with higher levels of import penetration, employment and labor productivity. In contrast, higher GDP growth and price growth are associated with lower probabilities of receiving protection.

B. Productivity Measures

I calculate productivity in two ways. The first is the superlative TFP index from Caves et al. (1982). As described in Aw, Chen and Roberts (2001), this TFP expression measures the performance of each plant, relative to a hypothetical plant producing the mean level of output with the mean level of inputs, within an industry, in the base period, 1987.[17] The TFP index therefore incorporates a plant's deviation of output and inputs from the industry mean in any given year, but also from the mean in the base period. This calculation yields a TFP measure that is comparable across plants and years:

[17] This measure of total factor productivity is standard in the trade and productivity literatures and has been used in other studies including Bernard, Redding and Schott (2008).

$$(1)\ \ln TFP_{pt}^{i} = (\ln Y_{pt}^{i} - \ln \overline{Y}_{t}^{i}) + \sum_{s=2}^{t} (\ln \overline{Y}_{t}^{i} - \ln \overline{Y}_{t-1}^{i})$$

$$-[\sum_{m} \frac{1}{2} (S_{mpt}^{i} + \overline{S}_{mt}^{i})(\ln X_{mpt}^{i} - \ln \overline{X}_{mt}^{i})$$

$$+ \sum_{s=2}^{t} \sum_{m} \frac{1}{2} (\overline{S}_{mt}^{i} + \overline{S}_{mt-1}^{i})(\ln \overline{X}_{mt}^{i} - \ln \overline{X}_{mt-1}^{i})]$$

I construct the TFP index expressed in Equation (1) for each plant *p* in year *t* using the set of inputs *m*={Capital, Raw Materials, Production Workers, Non-Production Workers}. The superscript *i* indicates that mean variables are calculated at the SIC4 industry level. X_{mpt}^{i} is the expenditure of plant p in time t on input m and S_{mpt}^{i} is the share of input m in total revenue. I calculate average input usage and shares at the industry-year-level. Therefore, $\overline{S}_{mt}^{i}$, $\ln \overline{Y}_{t}^{i}$ and $\overline{X}_{mt}^{i}$ are the arithmetic means of industry-level input shares, revenue and input expenditure, respectively.

The second measure of productivity is a simple, single-factor labor productivity, defined as the real total value of sales (RTVS) per employee:

$$(2)\ LP_{pt} = \frac{RTVS_{pt}}{TE_{pt}}$$

where TE_{pt} is the total number of employees at plant p at time t. Labor productivity is used primarily as a robustness check for the results based on total factor productivity. All results reported in this paper hold for both TFP and labor productivity.

Semi-parametric estimators, including those developed by Olley and Pakes (1996) and Levinsohn and Petrin (2003) have been used extensively in recent papers studying the effects of changes in trade policy on TFP.[18] As has been established in this literature, these methods can be useful for correcting the simultaneity bias that arises when plants with high TFP consume more inputs and the selection bias associated with only observing surviving plants. These methods are not well-suited for use with the economic census data employed in this paper, however, due to their use of lagged input values in the TFP calculation. While it could be useful to calculate TFP using one of these semi-parametric methods if annual data were available, I will note that Van Biesebroeck (2004) finds that TFP measures derived from various methods tend to be highly correlated.

C. Deflation

Whenever productivity is calculated using either revenue or value-added data—i.e. data that contain both a price and a quantity component—it is important to separate changes in prices and mark-ups from changes in true productivity. This

[18] See, for example, Pavcnik (2002), Fernandes (2008) and Konings and Vandenbussche (2008).

separation becomes critically important when mark-ups and productivity could move in the same direction, as in the situation examined in this paper. While some have suggested that antidumping duties can increase productivity, through their influence on technology adoption decisions, they almost certainly lead to higher mark-ups as well. Without an adjustment to account for changes in mark-ups, an increase in prices resulting from antidumping protection would show up as an increase in observed total factor productivity. This means that the results are biased toward finding a positive correlation between antidumping protection and revenue TFP.

The CMF, which collects output data in units of quantity for a subset of plants is uniquely suited for separating changes in prices and mark-ups from changes in physical productivity. In instances in which quantity data are available, physical quantities can be used as a measure of plant-level output and incorporated into the calculation of physical productivity, without deflation.

When calculating revenue productivity, I control for changes in mark-ups—to the extent possible—by deflating revenue using industry-level price indexes, applied to the set of products produced at each plant. This technique results in a plant-level deflator that is constructed by weighting the industry-level deflators according the share of a plant's output that is assigned to that industry. Industry-level output deflators, as well as industry-level deflators for cost of materials and capital are from the NBER-CES Manufacturing database reported in Bartelsman, Becker and Gray (2000).

There are at least two ways in which these plant-level deflators are insufficient for completely separating changes in mark-ups from changes in true productivity. First, since they are based on average price indexes, they do not allow for heterogeneity in pricing across plants. In this sense, plants that charge high prices—due to high local market power, for example—would be misinterpreted as high-productivity plants. Second, because the price indexes are calculated at the industry, rather than the product level, they will not fully reflect increases in product-level prices. This higher level of aggregation means that revenue-based productivity measures will overstate productivity growth in situations where mark-ups are increasing, as is likely the case in the situation considered in this paper.

D. Effective Antidumping Duty Rates

A single antidumping investigation can be filed against imports from multiple countries and if the case ends with a determination by the DOC and ITC to offer protection, each country may be assigned a different ad-valorem antidumping duty. Naturally, imports from certain countries account for larger shares of U.S. imports of a good than others. In order to account for the true importance of an antidumping duty on U.S. trade, therefore, I calculate an effective antidumping duty rate for each product that is assigned an ad-valorem antidumping duty. The effective antidumping rate is calculated as follows:

$$Rate_{gt} = \sum_{c} SHARE_{c,g,t-1} * AVD_{c,g,t}$$

where $SHARE_{c,g,t-1}$ is country c's share of U.S. imports of product g in time t-1 and $AVD_{c,g,t}$ is the ad-valorem duty applied to imports of product g from country c in time t. A country's share is calculated based on imports in time t-1, rather than time t, because antidumping duties often lead to significant reductions in imports from pre-protection levels. Using a pre-protection share, therefore, provides a more accurate representation of a country's importance to U.S. trade.

Research Questions

A. Do Temporary Tariffs Increase or Decrease Plant-Level Productivity?

As discussed above, some have argued that temporary protection can increase within-plant productivity by increasing the incentive to invest in new technology. On the other hand, temporary protection is also likely to lead to higher prices and mark-ups. Because an increase in revenue-based productivity that occurs at the time of protection could be caused by either of these phenomena, however, it can be difficult to determine what is driving gains in revenue productivity. Using output data measured in units of quantity, I am able to separate these two effects by calculating both revenue and physical productivity measures. Moreover, I am able to directly measure the effects of antidumping duties on plant-level prices and mark-ups. I find that apparent growth in productivity associated with antidumping protection is driven primarily by higher prices and mark-ups, rather than increases in true productivity.

Empirical Strategy

I examine the effect of temporary protection on plant-level productivity, prices and mark-ups using a difference-in-difference approach. As discussed above, the treatment group is composed of plants producing products that receive antidumping protection. I will consider three control groups, including the termination control group composed of plants that applied for, but did not receive protection and the two matched control groups. The goal of the difference-in-difference methodology is to isolate the effect of the treatment—antidumping protection—by eliminating time-invariant differences between the treatment and control group, as well as time-specific effects common to both treatment and control. The difference-in-difference estimator, therefore, measures not simply the change in the dependent variable that occurs following antidumping protection, but rather measures the difference between the changes in the treatment group and the changes in the control group.

Let T be the set of plants producing products that receive antidumping protection and let C be the set of plants in a particular control group. Further, define I_g to be the date that the antidumping investigation is initiated for product g. I measure the difference-in-difference effect by estimating Equation (3):

(3) $Prod_{pgt} = \alpha + \beta_1 Treatment_{pgt} * Post_{pgt} + \gamma_t + \delta_g + \varepsilon_{pt}$, where

$Treatment_{pgt} = 1 \ \forall \ p \in T$ and $Treatment_{pgt} = 0 \ \forall \ p \in C$

$Post_{pgt} = 1 \ \forall \ t > I_g$, 0 otherwise[19]

Here, $Prod_{pgt}$ is productivity—measured in TFP or Labor Productivity—at plant p, which produces product g at time t. Year fixed effects capture any macro-level shocks affecting plants in T and C equally. Similarly, product fixed effects, δ_g, capture time-invariant differences between products. Note that Equation (3) contains product-level fixed effects, rather than a more general *Treatment* dummy used in the most basic difference-in-difference expressions. This specification captures time-invariant differences between producers of different products *within T and C*. This is

[19] In general, antidumping protection lasts for ten years or more, meaning that almost every antidumping duty put in place during the sample period considered was still in effect at the end of the period. In 3 of the 198 antidumping investigations considered in this sample, however, antidumping protection began prior to 1992, but ended prior to 1997.

likely important when dealing with a diverse set of manufacturers from different sectors and industries. Finally, the coefficient β_1 on the interaction term is the coefficient of interest and measures the difference-in-difference effect of antidumping protection on the plant-level outcomes discussed below.

Equation (3) defines protection with a binary variable—any plant that receives any antidumping protection is considered to be equally protected. It seems reasonable to expect, however, that plants' reactions to protection would depend not only on this simple binary classification, but also on the level of protection they receive. That is, plants producing products that receive high ad-valorem duty rates—such as the 259.17 percent antidumping duty rate on Aluminum Sulfate from Venezuela—may respond differently than those producing products that receive low antidumping duty rates, such as the 2.98 percent rate on Collated Roofing Nails from Taiwan. As these two examples indicate, the variation in duty rates among cases that receive protection is large: the mean is 64 percent and the standard deviation is 60 percent.

I measure the effects of heterogeneity in antidumping rates by augmenting Equation (3) with an additional interaction term:

(4) $Prod_{pgt} = \alpha + \beta_1 Treatment_{pgt} * Post_{pgt} + \beta_2 Rate_{pgt} * Post_{pgt} + \gamma_t + \delta_g + \varepsilon_{pt}$

Here, $Rate_{pgt}$ is the ad-valorem effective antidumping duty rate on product *g*, which is produced by plant *p* at time *t*. By interacting $Rate_{pgt}$ with the $Post_{pgt}$ dummy, I am able to separate the effect of varying rates of protection from the mean response of all plants receiving antidumping protection.[20]

Equations (3) and (4) provide within-product estimates of the effect of antidumping duties on plants. It is important to note, however, that these results do not necessarily reflect the within-plant effect of antidumping duties. Because equations (3) and (4) are estimated on an unbalanced panel, coefficient estimates could reflect changes in mean plant-level productivity due to entry in exit. In order to estimate the within-plant effect of antidumping duties, I re-estimate equations (3) and (4) with plant fixed effects for the balanced subsample of plants producing in all three census years. These estimates provide both a useful robustness check for the within product-group estimates, as well an explicit estimate of the within-plant effects of antidumping duties.

[20] The *Treatment* binary variable is redundant in this specification because all treated plants have effective duty rates greater than zero. Control plants have effective duty rates that are equal to zero.

Lastly, I will employ the difference-in-difference framework in equations (3) and (4) to examine the effect of antidumping duties on plant-level prices, as well as mark-ups over average total cost. Prices are defined as follows:

$$P_{pgt} = \frac{TVS_{pgt}}{Q_{pgt}}$$

where *TVS* is a plant's total value of shipments and *Q* is the total quantity of units shipped. Plant-level mark-ups over average total cost are defined as:

$$PATC_{pgt} = \frac{P_{pgt}}{ATC_{pgt}}$$

where $ATC_{pgt} = \dfrac{Wages_{pgt} + CM_{pgt} + RTAE_{pgt}}{Q_{pgt}}$

Here, *Wages* are the wages paid to production workers, *CM* is the cost of materials and *RTAE* is real total value of assets, or capital.

Results

Revenue Productivity

I do find that antidumping protection is associated with increases in revenue productivity of 5 to 8 percent, as shown in Table 5.[21] The first two columns of Table

[21] Tables 5 and 6 report results based on the termination control group of plants producing products that applied for, but were turned down for protection.

5 report the results for equation (3) with TFP and labor productivity and the next two report results for the same specification, with state fixed effects. The final four columns of Table 5 report results from estimation of equation (4), which includes the interaction term accounting for variation in the effective antidumping duty rate. I continue to find a positive and significant relationship between antidumping protection and revenue productivity when the effective duty rate is included in the specification, although the rate term is not significant.

In Table 6, I report the equivalent results when estimating equations 3 and 4 with plant fixed effects on the balanced subsample. As discussed above, these within-plant estimates are unaffected by changes in the composition of plants in the product-group caused by entry and exit. The results are consistent with those obtained with product fixed effects, with protected plants exhibiting increases in plant-level productivity of 3 to 6 percent. In sum, the estimates reported in Tables 5 and 6 appear to support the argument that antidumping duties can bring about increases in plant-level productivity. These results are also robust to consideration of the two matched control groups, as can be seen in Tables 5a and 6a.[22]

[22] The increase in revenue productivity associated with antidumping protection—as measured by the binary protection variable—is a robust result in this analysis. It is somewhat surprising, however, that revenue productivity appears to be essentially

Physical Productivity

As described above, the use of revenue-based productivity measures can yield misleading results in situations where prices and mark-ups may also be changing concomitantly. In particular, because the imposition of antidumping duties likely allows domestic producers to increase prices and mark-ups, revenue productivity measures will overstate any potential productivity gains associated with antidumping protection. Because the CMF contains output data measured in units of quantity for a subset of products, I am able to calculate measures of physical productivity that are unaffected by changes in prices and mark-ups.

The effect of antidumping duties on plant-level productivity is starkly different when output is measured in units of quantity, rather than revenue. As reported in Table 7, antidumping duties are actually associated with a decrease in physical productivity among the set of plants reporting quantity data. In fact, physical productivity actually falls by a greater amount as the effective duty rate protecting the plant increases. This effect persists when estimating the difference-in-

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unaffected by changes in the antidumping duty rate. As will be seen in results below, however, this lack of responsiveness appears to be due to decreases in physical productivity associated with higher antidumping duty rates being offset by increases in prices and mark-ups.

difference specification with plant fixed effects on the balanced subsample, as shown in Table 8. Tables 7a and 8a confirm that these results are robust to consideration of the two matched control groups, as well.

Bernard, Redding and Schott (2006) provides a plausible reason that plant-level productivity may fall in the treatment group, relative to the control group. In this model, tariff protection allows firms to continue producing low-productivity products that they would have otherwise stopped producing. Indeed—as will be discussed in more detail below—I do find that protected plants are less likely to drop investigated products than unprotected plants. This means that while plants in the control group focus on their "core competencies" and produce their highest-productivity products, plants in the treatment group are able to continue producing low-productivity products. As a result, within-plant productivity increases more in the control group than in the treatment group.

A word of warning in terms of interpreting these results is necessary here. It would be inappropriate based on these results to claim that antidumping duties, *in general*, decrease plant-level physical productivity. It is true that antidumping duties were associated with a decline in productivity among the set of plants reporting output data in units of quantity. However, this group is not necessarily representative of the full set of plants subject to antidumping protection. First, as can be seen in Table 3, the distribution of plants across 2-digit SIC sectors is somewhat different for the set of plants reporting quantity data, than for the overall sample. Second, when I examine the effect of antidumping protection on the revenue productivity of the subset of plants reporting output in units of quantity, I find that revenue productivity was unaffected by antidumping protection. This contrasts with the increase in revenue productivity associated with antidumping protection in the full sample. Nonetheless the fact that plants in this sub-sample experienced a zero effect of antidumping protection on revenue productivity and a large and highly significant decrease in physical productivity suggests that increases in prices and mark-ups are affecting results based on revenue productivity.[23]

Prices and Mark-Ups

The disparity between results showing the effect of antidumping protection on revenue versus physical productivity suggests that increases in prices and mark-ups are playing a role in the apparent increase in revenue productivity. I use the

[23] An alternative explanation is that plants receiving antidumping protection increase the quality of the products they produce. This seems unlikely, given that the products for which the Census Bureau collects quantity data tend to be commodities, with little room for quality improvement. Nonetheless, exploration of the effect of antidumping duties on product-quality will be an interesting aspect of my future research.

same difference-in-difference specifications from the productivity analysis to examine the effects of antidumping duties on the measures of prices and mark-ups over average total cost described above.

As reported in Table 9, I find that antidumping duties are associated with price increases of 27 to 36 percent. Moreover, these pricing changes are sensitive to the effective duty rate a plant experiences—the higher the effective duty rate, the higher the prices charged by the plant. These results hold for both within-product-group and within-plant estimators. Table 10 reports the effects of antidumping protection on mark-ups over average total cost. I find that antidumping duties increase mark-ups over average total cost by 7 percent. Moreover, the magnitude of the mark-ups over average total cost increases as the effective duty rate increases in the within-product estimates. The relationship between the effective duty rate and the level of mark-ups does not hold in the within-plant specifications, however. These results are robust to consideration of the two matched control groups, as can be seen in Tables 9a and 10a.

B. Do Temporary Tariffs Discourage Product-Dropping?

Bernard, Redding and Schott (2006) shows that reductions in trade barriers can increase firm or plant-level productivity by inducing firms to drop their least productive products, while expanding output of their most productive products.

Moreover, product-dropping can yield increases in aggregate productivity—as defined below—as the least productive plants drop products. In fact, I do find that antidumping protection decreases the probability of dropping investigated products.

Empirical Strategy

The effect of antidumping duties on the probability of dropping products is investigated using a difference-in-difference specification similar to that employed to study changes in plant-level productivity, prices and mark-ups. By comparing the probability of product-dropping among protected plants to the unprotected plants in the three control groups, I am able to estimate the effect of antidumping duties on product-dropping.

An important difference between this product-switching analysis and the plant-level productivity regressions described above is that the product-switching data are defined at the plant-product-level. This means that I have dropped the restriction that each plant is assigned to a particular treatment or control product. In doing so, I am able to consider the full set of products that are involved in antidumping investigations. I employ a linear probability model, to allow for the inclusion of fixed effects and clustering of standard errors and estimate the following two equations:

(5) $Drop^{i}_{pgt} = \alpha + \beta_1 Treatment^{i}_{pgt} * Post^{i}_{pgt} + \beta_2' X^{i}_{pgt} + \gamma_t + \delta_g + \varepsilon^{i}_{pgt}$

(6)

$$Drop^{i}_{pgt} = \alpha + \beta_1 Treatment^{i}_{pgt} * Post^{i}_{pgt} + \beta_2 Post^{i}_{pgt} * Rate^{i}_{pgt} + \beta_3' X^{i}_{pgt} + \gamma_t + \delta_g + \varepsilon^{i}_{pgt}$$

Drop is a binary variable that equals 1 if product g is produced by plant p at time t, but not time t+5. *X* is a matrix of plant-product-level variables found to be determinants of product-dropping in Bernard, Redding and Schott (2008), namely the product-level value of shipments and the number of years a product has been produced (tenure). The superscript i denotes that the data are at the plant-product level. To be clear, the variable *Drop* only takes into account product-dropping by continuing plants. Exiting plants are not considered product-droppers.

Results

I find that plants are 6 percent less likely to drop protected products than they are to drop unprotected products, as reported in Table 11. Moreover, this product-switching behavior is sensitive to the value of the effective duty rate applied to a product. I find that the probability of dropping a protected product decreases as the effective duty rate assigned to that product increases. In the product-dropping regression, the results are robust to the inclusion of product-level shipments and product tenure, which are both negative and significant, as expected. These results make clear that more plants produce a given protected product than would be the case if the product was unprotected. They are also robust to consideration of the two matched control groups, as can be seen in Tables 11A and 11B.

This reduction in product-switching brought about by antidumping duties has implications for both plant-level and aggregate productivity. At the plant level, Bernard, Redding and Schott (2006) suggests that a reduction in product-dropping resulting from trade protection will lower productivity, relative to unprotected plants. While unprotected plants drop their least productive products to focus on their highest-productivity product-lines, protected plants continue to produce the protected product, resulting in lower relative productivity. A reduction in product-dropping among protected plants can also decrease aggregate productivity growth. In unprotected product-groups, the least productive producers will either exit completely, or drop the unprotected product. In the protected product groups, however, these low-productivity plants are able to continue producing, resulting in lower aggregate productivity relative to the control group.

C. Do Temporary Tariffs Discourage Plant-Level Exit?

It is a well-known result that trade protection can slow aggregate productivity growth by preventing the exit of low-productivity plants and firms that would otherwise cease to operate. I examine this question by comparing the probability of plant-level exit in the treatment group of protected plants to that in the control group. I find that antidumping duties do not affect the probability of exit. Plants that are denied protection by the government are no more likely to exit than those that receive antidumping duties.

Empirical Strategy

I define a plant as exiting in year t if it appears in the CMF in year *t*, but not in year *t+5*. To be clear, a plant that halts production of the investigated product between year *t* and year *t+5*, but continues to operate, is not counted as an exit. A binary exit variable is defined in this way for the years 1987 and 1992. The exit variable is missing in 1997 due to a change in product-classification system that makes it difficult to track plant survival from 1997 to 2002.

I estimate the relationship between antidumping protection and the probability of exit using a difference-in-difference framework identical to the specification used to study changes in product-dropping above. As in the analysis of product-dropping, I employ a linear probability model, to allow for the inclusion of fixed effects and clustering of standard errors:

(7) $Exit_{pgt} = \alpha + \beta_1 Treatment_{pgt} * Post_{pgt} + \gamma_t + \delta_g + \varepsilon_{pt}$

The binary dependent variable, *Exit* was described above. The coefficient β_1 is the primary parameter of interest and estimates the effect of receiving antidumping protection on the probability of exit. As in Equation (3), year and product-group fixed effects are included. Estimates with robust standard errors and clustering at the product-group level are reported in Table 12.

Next, I expand Equation (7) to include plant-level variables that have been found to be important determinants of exit in the large empirical literature on the effects of changes in trade costs on exit. Using determinants of exit from Bernard, Jensen and Schott (2006), I estimate Equation (8):

(8) $Exit_{pgt} = \alpha + \beta_1 Treatment_{pgt} * Post_{pgt} + \beta' X_{pgt} + \gamma_t + \delta_g + \varepsilon_{pt}$

where X is a matrix of plant-level variables including log of total employment, plant age, log of capital-labor ratio, log of average wage and indicators for whether the plant is a multi-product plant, or a part of a multi-unit firm. Lastly, I re-estimate Equations (7) and (8) with the *Rate*Post* interaction variable used to estimate the effect of variation in the effective antidumping duty rate.

Results

Results are reported in Table 12. While I do find in one specification that higher effective duty rates decrease the probability of exit, the result is not robust. In particular, it disappears when the additional control variables commonly used in analyses of exit are included. Moreover, the magnitude of the coefficient is small. A one percent increase in the effective duty rate decreases the probability of exit by only 0.3 percent. It appears, therefore, that plants that are turned down for protection are no less likely to exit than those receiving protection. Combined with the product-dropping result described above, this suggests that U.S. manufacturers are flexible and dynamic in the face of changes in trade policy. Rather than exiting, they react to being turned down for antidumping duties by dropping the unprotected product and shifting resources to other, potentially higher-productivity products. There is also no effect of antidumping protection on the probability of exit when considering the two matched control groups, as can be seen in Tables 12A and 12B.

D. Do Temporary Tariffs Decrease Output Rationalization and Aggregate Productivity?

A number of theoretical models including Melitz (2003) and Bernard, Redding and Schott (2006) predict that tariff increases allow for the continued operation of low-productivity firms that might otherwise stop production. If antidumping duties create a similar situation, we should expect the level of output rationalization to increase in the control group relative to the treatment group.

Indeed, I do find that the level of output rationalization rises in the control group and falls among the protected plants in the treatment group.

Empirical Strategy

I have already shown that antidumping duties allow plants that would have otherwise dropped the investigated product to continue producing. If these plants that would have otherwise dropped the product are also low-productivity plants, antidumping duties may have a negative effect on output rationalization and aggregate productivity growth. To compare the productivity of product-dropping plants to non-droppers, I regress plant-level productivity on a binary variable that equals one in time t if plant p dropped an investigated product between time t and time t+5:

(12) $Prod_{pgt} = \alpha + \beta_1 Drop_{pgt} + \gamma_t + \delta_g + \varepsilon_{pt}$

Next, I examine the level of output rationalization directly by decomposing aggregate productivity as in Olley and Pakes (1996), Pavcnik (2002) and Fernandes (2007). This procedure decomposes growth in aggregate productivity into two components, shown below:

(13) $W_{gt} = \sum_p s_{pgt} TFP_{pgt} = TFP_{tg}^{mean} + (s_{pgt} - s_{gt}^{mean})(TFP_{pgt} - TFP_{gt}^{mean})$

The first term of the final expression represents mean plant-level productivity at time t. The second term is a covariance-like variable representing the degree to which greater output is produced by higher-productivity plants. s_{pgt} denotes the share of plant *p*'s output in the total output of product-group *g* at time t, while s_{gt}^{mean} is the mean output share of plants producing product *g* at time *t*. Similarly, TFP_{pgt} and TFP_{gt}^{mean} represent the revenue total factor productivity of plant *p* and the mean TFP of plants in product-group *g*, respectively. When plants with above-average TFP also capture an above-average market share, the covariance term increases, indicating a higher level of output rationalization.

The covariance term measuring the degree of output rationalization will be the primary variable of interest. Ideally, I would simply examine the effects of antidumping duties on aggregate productivity, W_{gt} directly. A number of data problems would make this comparison unreliable, however. First, as mentioned above, the use of revenue-based aggregate productivity measures would overstate productivity gains among protected product-groups, since I have shown that protected plants respond to temporary protection by increasing prices. Moreover, quantity-based productivity measures are not useful in settings where analysis is taking place at the product-group level or higher, since quantity data are only available for producers of a limited set of products.

The use of revenue-based productivity measures is less problematic for analyzing output rationalization. Assuming that prices increase uniformly among all producers of a given product once it receives protection, the covariance term will still accurately reflect the degree of output rationalization within a product group. After calculating aggregate productivity, mean plant-level productivity and the output rationalization term at the product-group-level, I report their output-weighted means by year, treatment group and a dummy variable indicating whether the antidumping investigation for product g has already taken place. The results of the decomposition described are reported in Table 14.

Results

First, I find that plants that drop the investigated product have lower productivities than non-dropping plants, as reported in Table 13. As a result, the reduction in product-dropping by low-productivity plants caused by antidumping duties may contribute to a decrease in output rationalization and aggregate productivity growth among protected product-groups.

Indeed, I do find that antidumping protection decreased the level of output rationalization in the treatment group, while output rationalization grew in the control group. As reported in Table 14, the treatment group of plants that ultimately receive protection starts with a level of output rationalization in 1987 that is higher than the control group. As time progresses and protection takes effect, however, output rationalization falls in the treatment group—likely due to continued operation by low-productivity plants that would have otherwise dropped the investigated product—and rises in the control group. By 1997, the control group has overtaken the treatment group in terms of output rationalization. By preventing the reallocation of resources that takes place as a result of trade liberalization, therefore, antidumping duties contribute to a reduction in aggregate productivity.

Section 5: Conclusions

Antidumping duties have become one of the primary forms of trade protection world-wide, and the large magnitudes of the duties imposed can dramatically alter trade flows. Yet despite the growing importance of antidumping duties to international trade, there is little understanding of their effects at the micro level. In addition to increasing our understanding of an important trade policy, the study of antidumping duties can also provide new insights into some of the best-known results in the literature examining the heterogeneous responses of firms to trade liberalization.

Using a difference-in-difference framework, I compare outcomes at plants in the treatment group that receives protection to those in the three control groups that did not. I find that apparent increases in revenue productivity associated with antidumping protection are driven primarily by increases in prices and mark-ups. Physical productivity actually falls among the protected plants reporting output data in units of quantity. Protected plants are also less likely to drop protected products, although they are no less likely exit. Because antidumping protection allows for the continued operation of low-productivity plants that might have otherwise dropped the protected product, antidumping duties decrease the level of output rationalization, with low-productivity plants expanding their market shares.

The results have several implications. First, for empirical researchers, the results underscore the importance of differentiating between changes in revenue productivity—which may be driven by increases in prices and mark-ups—and changes in physical productivity. Separating these two effects is particularly important in situations where changes in productivity may be taking place concomitantly with changes in prices, as is the case with antidumping duties. Second, for theoretical researchers, the results underscore the importance of thinking of plants and firms as producers of multiple products. While antidumping duties had no effect on the probability of plant exit, they had a clear impact on plants' product mix. And finally, for policy-makers, the results suggest that antidumping protection does not offer a free lunch in the form of higher plant-level productivity. Offering antidumping protection comes at a cost that is incurred by consumers, in the form of higher prices.

Table 1: Antidumping Investigations by HTS Chapter, 1988-1996

HTS2	Description	Investigations
73	Articles of Iron and Steel	27
72	Iron and Steel	20
84	Machinery	16
28	Inorganic Chemicals	14
85	Electrical Machinery	13
29	Organic Chemicals	12
87	Transportation Vehicles and Parts	11
90	Precision Instruments and Apparatus	8
39	Plastics and Articles Thereof	6
25	Plastering, Lime and Cement	5
81	Other Base Metals	5
30	Pharmaceutical Products	4
40	Rubber and Articles Thereof	4
56	Certain Textiles	4
83	Misc. Articles of Base Metal	4
Other		45
Total		198

Notes: This table displays the number of antidumping investigations by 2-digit Harmonized Tariff System Category. Investigations involving products in more than one 2-digit HTS category are counted in each relevant category.

Table 2: All Antidumping Cases, by Outcome and SIC2

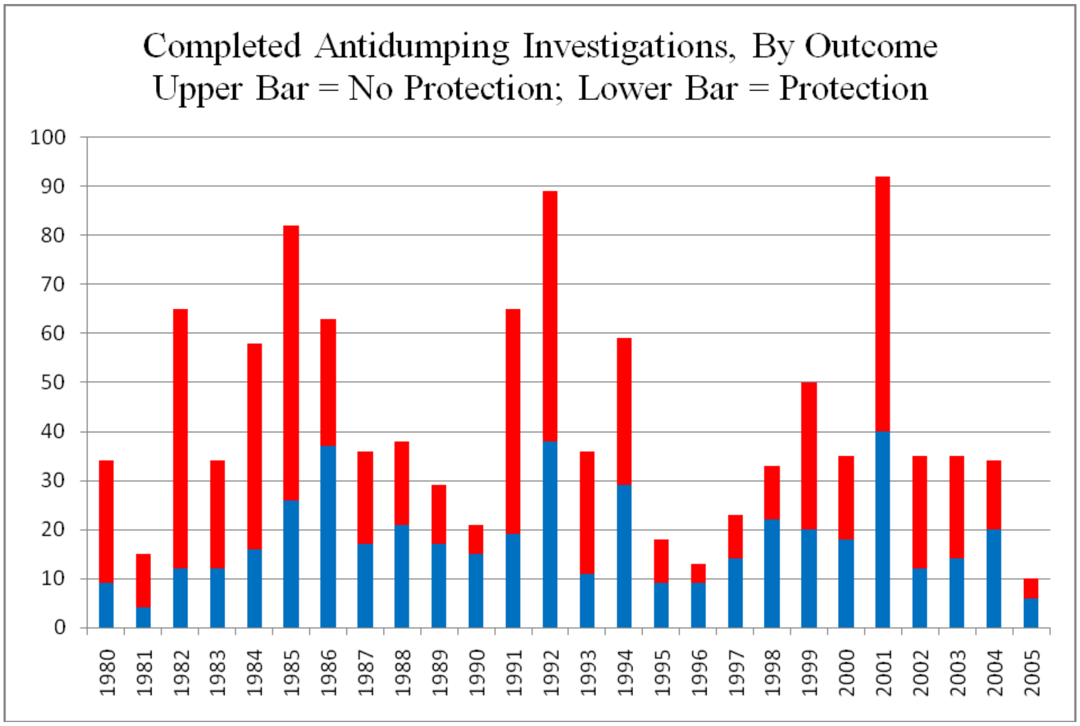


Table 3: Plant-Level Observations, by SIC2

	Total Observations				Observations With Quantity			
SIC2 Description	SIC2	Control	Treatment	Total	SIC2	Control	Treatment	Total
Food and Kindred Spirits	20	163	1,462	1,625	20	132	1,096	1,228
Textile Mill Products	22	1,061	891	1,952	22	757	415	1,172
Apparel	23	8,283	1,725	10,008	23	928	532	1,460
Paper Products	26	2,602	0	2,602	26	1,065	0	1,065
Chemical Products	28	815	3,566	4,381	28	77	652	729
Rubber Products	30	13,681	2,996	16,677	30	170	14	184
Leather Products	32	2,081	582	2,663	32	451	396	847
Primary Metals	33	468	3,266	3,734	33	*	1,971	*
Fabricated Metals	34	13,244	4,318	17,562	34	1,038	500	1,538
Industrial Machinery	35	3,884	16,066	19,950	35	180	314	494
Electronic Machinery	36	650	7,540	8,190	36	91	35	126
Transport Equipment	37	2,869	889	3,758	37	723	*	*
Measuring Instruments	38	75	3,071	3,146	38	25	*	*
Misc. Manufacturing	39	0	413	413	39	0	88	88

Notes: This table reports the number of plant-level observations in the treatment group (applied and received protection) and control group (applied but did not receive protection), by 2-digit SIC (1987) category. In addition, the table shows the number of plant-level observations where output data were reported in units of quantity by treatment status and SIC2. An asterisk (*) denotes a cell that was suppressed to prevent the disclosure of confidential data.

Table 4: Summary Statistics by Treatment Group, Year

Year	Treatment	Total Sales	No. Employees	Capital Intensity	No. Plants	Qty. Share	Treatment Share	Effective AD Rate
1987	0	23,596	142	41	15,007	93%	70%	
1987	1	23,437	165	53	14,598	93%	68%	14%
1992	0	26,250	122	46	17,092	93%	69%	
1992	1	28,703	149	56	15,588	92%	67%	13%
1997	0	33,234	119	52	17,778	93%	69%	
1997	1	38,025	146	73	16,599	92%	67%	13%

Year	Treatment	Revenue TFP	Revenue Labor Prod.	Physical TFP	Physical Labor Prod.
1987	0	0.14	4.68	-0.52	5.14
1987	1	0.14	4.63	0.30	5.65
1992	0	0.11	4.72	-0.02	5.48
1992	1	0.19	4.72	-0.06	5.43
1997	0	0.11	4.80	0.26	5.87
1997	1	0.29	4.89	-0.12	5.45

Notes: This table reports summary statistics by year and treatment status. A treatment of zero (0) denotes the control group and a treatment of one (1) denotes the treatment group. Capital intensity is the book value of capital divided by the number of employees.

Table 5: Antidumping Duties and Revenue Productivity – Within Product-Group Estimators
Termination Control Group

	TFP	LP	TFP	LP	TFP	LP	TFP	LP
Treatment*Post	0.06**	0.05**	0.06**	0.05**	0.08**	0.06**	0.08**	0.06**
	0.03	0.02	0.03	0.02	0.03	0.02	0.03	0.02
Post*Rate					-0.001	-0.001	-0.001	-0.001
					0.002	0.001	0.002	0.001
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Product FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	No	No	Yes	Yes	No	No	Yes	Yes
Observations	96,662	96,662	96,662	96,662	96,662	96,662	96,662	96,662
R-Squared	0.666	0.309	0.668	0.313	0.666	0.39	0.668	0.313

Notes: This table summarizes OLS regression coefficients of plant-level total factor productivity (TFP) and labor productivity (LP) on the difference-in-difference interaction term "Treatment*Post" and the effective duty rate interaction term "Post*Rate." Robust standard errors are reported below each coefficient after adjustment for clustering at the product-level. ***, ** and * represent statistical significance at the 1%, 5% and 10% levels, respectively.

Table 5A: Antidumping Duties and Revenue Productivity – Within Product-Group Estimators
Matched Control Groups

	Matched Control Group 1				Matched Control Group 2			
	TFP	LP	TFP	LP	TFP	LP	TFP	LP
Treatment*Post	0.10***	0.10***	0.11***	0.11***	0.08**	0.06***	0.10***	0.07***
	0.04	0.02	0.04	0.03	0.03	0.02	0.03	0.02
Post*Rate			-0.001	-0.001			-0.0011	-0.001
			0.003	0.002			0.0022	0.001
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Product FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	131,730	131,730	131,730	131,730	84,857	84,857	84,857	84,857
R-Squared	0.797	0.418	0.797	0.418	0.66	0.317	0.66	0.317

Notes: This table summarizes OLS regression coefficients of plant-level total factor productivity (TFP) and labor productivity (LP) on the difference-in-difference interaction term "Treatment*Post" and the effective duty rate interaction term "Post*Rate." Robust standard errors are reported below each coefficient after adjustment for clustering at the product-level. ***, ** and * represent statistical significance at the 1%, 5% and 10% levels, respectively.

Table 6: Antidumping Duties and Revenue Productivity – Within Plant Estimators
Termination Control Group

	TFP	LP	TFP	LP
Treatment*Post	0.0487***	0.0256***	0.0632***	0.0312***
	0.0104	0.0082	0.0124	0.0098
Post*Rate			-0.0011**	-0.0004
			0.0005	0.0004
Year FE	Yes	Yes	Yes	Yes
Plant FE	Yes	Yes	Yes	Yes
Observations	27,699	27,699	27,699	27,699
R-Squared	0.909	0.874	0.99	0.874

Notes: This table summarizes OLS regression coefficients of plant-level total factor productivity (TFP) and labor productivity (LP) on the difference-in-difference interaction term "Treatment*Post" and the effective duty rate interaction term "Post*Rate." Robust standard errors are reported below each coefficient after adjustment for clustering at the plant-level. ***, ** and * represent statistical significance at the 1%, 5% and 10% levels, respectively.

Table 6A: Antidumping Duties and Revenue Productivity – Within Plant Estimators
Matched Control Groups

	Matched Control Group 1				Matched Control Group 2			
	TFP	LP	TFP	LP	TFP	LP	TFP	LP
Treatment*Post	0.08***	0.08***	0.10***	0.09***	0.04***	0.02**	0.06***	0.03**
	0.001	0.01	0.01	0.01	0.01	0.008	0.01	0.01
Post*Rate			-0.004**	-0.0001			-0.001**	-0.001
			0.001	0.0005			0.005	0.0004
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Plant FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	40,374	40,374	40,374	40,374	24,471	24,471	24,471	24,471
R-Squared	0.945	0.895	0.945	0.895	0.913	0.874	0.913	0.874

Notes: This table summarizes OLS regression coefficients of plant-level total factor productivity (TFP) and labor productivity (LP) on the difference-in-difference interaction term "Treatment*Post" and the effective duty rate interaction term "Post*Rate." Robust standard errors are reported below each coefficient after adjustment for clustering at the product-level. ***, ** and * represent statistical significance at the 1%, 5% and 10% levels, respectively.

Table 7: Antidumping Duties and Physical Productivity – Within Product-Group Estimators
Termination Control Group

	Physical Productivity Measures				Revenue Productivity Measures			
	TFPQ	LPQ	TFPQ	LPQ	TFP	LP	TFP	LP
Treatment*Post	-0.39*	-0.43**	0.22	0.16	0.005	-0.03	0.05	0.004
	0.22	0.21	0.18	0.17	0.070	0.03	0.07	0.042
Post*Rate			-0.03***	-0.03***			-0.002	-0.002
			0.005	0.005			0.002	0.002
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Product FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	11,526	11,526	11,526	11,526	11,526	11,526	11,526	11,526
R-Squared	0.643	0.62	0.646	0.623	0.868	0.451	0.868	0.451

Notes: This table summarizes OLS regression coefficients of plant-level productivity on the difference-in-difference interaction term "Treatment*Post" and the effective duty rate interaction term "Post*Rate." The first four columns show regression results using measures of physical productivity as the dependent variable, for the subset of plants reporting quantity-based output data. The last four columns show regression results using measures of revenue productivity as the dependent variable, for the same subset of plants. TFPQ denotes physical total-factor-productivity and LPQ denotes physical labor productivity. Robust standard errors are reported below each coefficient after adjustment for clustering at the product-level. ***, ** and * represent statistical significance at the 1%, 5% and 10% levels, respectively.

Table 7A: Antidumping Duties and Physical Productivity – Within Product-Group Estimators
Matched Control Groups

	Matched Control Group 1				Matched Control Group 2			
	TFPQ	LPQ	TFPQ	LPQ	TFPQ	LPQ	TFPQ	LPQ
Treatment*Post	-0.43*	-0.42*	0.12	0.09	-0.40*	-0.47**	0.22	0.12
	0.26	0.23	0.22	0.21	0.24	0.21	0.19	0.18
Post*Rate			-0.03**	-0.03**			-0.03***	-0.03***
			0.01	0.01			0.005	0.005
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Product FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7,220	7,220	7,220	7,220	10,086	10,086	10,086	10,086
R-Squared	0.647	0.612	0.651	0.616	0.639	0.611	0.643	0.614

Notes: These tables summarize OLS regression coefficients of plant-level physical productivity on the difference-in-difference interaction term "Treatment*Post" and the effective duty rate interaction term "Post*Rate." TFPQ denotes physical total-factor-productivity and LPQ denotes physical labor productivity. Robust standard errors are reported below each coefficient after adjustment for clustering at the product-level. ***, ** and * represent statistical significance at the 1%, 5% and 10% levels, respectively.

Table 8: Antidumping Duties and Physical Productivity – Within Plant Estimators
Termination Control Group

	Physical Productivity Measures				Revenue Productivity Measures			
	TFPQ	LPQ	TFPQ	LPQ	TFP	LP	TFP	LP
Treatment*Post	-0.29**	-0.20*	0.35**	0.37**	0.01	0.03	0.07	0.01
	0.11	0.11	0.16	0.15	0.03	0.03	0.04	0.04
Post*Rate			-0.04***	-0.03***			-0.003**	0.001
			0.01	0.01			0.002	0.001
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Plant FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,550	2,550	2,550	2,550	2,550	2,550	2,550	2,550
R-Squared	0.896	0.904	0.91	0.98	0.899	0.906	0.899	0.906

Notes: These tables summarize OLS regression coefficients of plant-level productivity on the difference-in-difference interaction term "Treatment*Post" and the effective duty rate interaction term "Post*Rate." The first four columns of each table show regression results using measures of physical productivity as the dependent variable, for the subset of plants reporting quantity-based output data. The last four columns show regression results using measures of revenue productivity as the dependent variable, for the same subset of plants. TFPQ denotes physical total-factor-productivity and LPQ denotes physical labor productivity. Robust standard errors are reported below each coefficient after adjustment for clustering at the plant-level. ***, ** and * represent statistical significance at the 1%, 5% and 10% levels, respectively.

Table 8A: Antidumping Duties and Physical Productivity – Within Plant Estimators
Matched Control Groups

	Matched Control Group 1				Matched Control Group 2			
	TFPQ	LPQ	TFPQ	LPQ	TFPQ	LPQ	TFPQ	LPQ
Treatment*Post	-0.60***	-0.39***	0.02	0.17	-0.36**	-0.31**	0.27	0.26
	0.15	0.14	0.17	0.17	0.14	0.14	0.18	0.17
Post*Rate			-0.04***	-0.03***			-0.04***	-0.03***
			0.01	0.01			0.01	0.01
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Plant FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,013	2,013	2,013	2,013	2,268	2,268	2,268	2,268
R-Squared	0.911	0.919	0.917	0.923	0.911	0.919	0.917	0.924

Notes: These tables summarize OLS regression coefficients of plant-level physical productivity on the difference-in-difference interaction term "Treatment*Post" and the effective duty rate interaction term "Post*Rate." TFPQ denotes physical total-factor-productivity and LPQ denotes physical labor productivity. Robust standard errors are reported below each coefficient after adjustment for clustering at the product-level. ***, ** and * represent statistical significance at the 1%, 5% and 10% levels, respectively.

Table 9: The Effect of Antidumping Duties on Plant-Level Prices
Termination Control Group

	Price	Price	Price	Price
Treatment*Post	0.42**	-0.16	0.27**	-0.35**
	0.20	0.17	0.11	0.15
Post*Rate		0.03***		0.04***
		0.00		0.01
Year FE	Yes	Yes	Yes	Yes
Product FE	Yes	Yes	No	No
Plant FE	No	No	Yes	Yes
Observations	11,526	11,526	2,550	2,550
R-Squared	0.66	0.66	0.90	0.91

Table 9A: The Effect of Antidumping Duties on Plant-Level Prices
Matched Control Groups

	Matched Control 1				Matched Control 2			
	Price	Price	Price	Price	Price	Price	Price	Price
Treatment*Post	0.38*	-0.15	0.36**	-0.24	0.44**	-0.14	0.32**	-0.30
	0.21	0.20	0.15	0.18	0.20	0.17	0.14	0.17
Post*Rate		0.03***		0.04***		0.03***		0.037**
		0.01		0.01		0.00		0.01
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Product FE	Yes	Yes	No	No	Yes	Yes	No	No
Plant FE	No	No	Yes	Yes	No	No	Yes	Yes
Observations	7,220	7,220	2,013	2,013	10,086	10,086	2,268	2,268
R-Squared	0.63	0.63	0.90	0.91	0.63	0.64	0.91	0.91

Notes: These tables summarize OLS regression coefficients of plant-level price on the difference-in-difference interaction term "Treatment*Post" and the effective duty rate interaction term "Post*Rate." Robust standard errors are reported below each coefficient after adjustment for clustering at the plant-level. ***, ** and * represent statistical significance at the 1%, 5% and 10% levels, respectively. Results with plant fixed effects are based on the balanced sub-sample of plants that were active in all three census years.

Table 10: The Effect of Antidumping Duties on Mark-Ups
Termination Control Group

	P/ATC	P/ATC	P/ATC	P/ATC
Treatment*Post	0.06**	0.037	0.07***	0.048
	0.024	0.029	0.024	0.032
Post*Rate		0.001		0.002
		0.001		0.002
Year FE	Yes	Yes	Yes	Yes
Product FE	Yes	Yes	No	No
Plant FE	No	No	Yes	Yes
Observations	11,526	11,526	2,550	2,550
R-Squared	0.30	0.33	0.69	0.69

Table 10A: The Effect of Antidumping Duties on Mark-Ups
Termination Control Group

	Matched Control 1				Matched Control 2			
	P/ATC	P/ATC	P/ATC	P/ATC	P/ATC	P/ATC	P/ATC	P/ATC
Treatment*Post	0.043	0.024	0.032	0.006	0.06**	0.040	0.06**	0.034
	0.034	0.038	0.034	0.037	0.027	0.032	0.028	0.033
Post*Rate		0.001*		0.002		0.0012*		0.002
		0.0006		0.002		0.0007		0.002
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Product FE	Yes	Yes	No	No	Yes	Yes	No	No
Plant FE	No	No	Yes	Yes	No	No	Yes	Yes
Observations	7,220	7,220	2,013	2,013	10,086	10,086	2,268	2,268
R-Squared	0.32	0.32	0.70	0.70	0.31	0.37	0.70	0.70

Notes: These tables summarize OLS regression coefficients of plant-level mark-up over ATC on the difference-in-difference interaction term "Treatment*Post" and the effective duty rate interaction term "Post*Rate." Robust standard errors are reported below each coefficient after adjustment for clustering at the plant-level. ***, ** and * represent statistical significance at the 1%, 5% and 10% levels, respectively.

Table 11: Antidumping Duties and the Probability of Product-Dropping
Termination Control Group

	Drop	Drop	Drop	Drop
Treatment*Post	-0.060***	-0.062***	-0.023	-0.025
	0.017	0.016	0.024	0.022
Post*Rate			-0.003**	-0.003**
			0.001	0.001
Product Shipments		-0.076***		-0.076***
		0.002		0.002
Product Tenure		-0.119***		-0.119***
		0.012		0.012
Year FE	Yes	Yes	Yes	Yes
Product FE	Yes	Yes	Yes	Yes
Observations	46,742	46,742	46,742	46,742
R-Squared	0.118	0.204	0.118	0.205

Table 11A: Antidumping Duties and the Probability of Product-Dropping
Matched Control Group 1

	Drop	Drop	Drop	Drop
Treatment*Post	-0.0515***	-0.0445***	-0.015	-0.007
	0.013	0.013	0.022	0.021
Post*Rate			-0.0028**	-0.0028**
			0.001	0.001
Product Shipments		-0.0475***		-0.0475***
		0.007		0.007
Product Tenure		-0.1484***		-0.1485***
		0.008		0.008
Year FE	Yes	Yes	Yes	Yes
Product FE	Yes	Yes	Yes	Yes
Observations	98,166	98,166	98,166	98,166
R-Squared	0.095	0.148	0.095	0.148

Notes: These tables summarize OLS regression coefficients of a binary variable indicating product-dropping (Drop) on the difference-in-difference interaction term "Treatment*Post" and the effective duty rate interaction term "Post*Rate." Robust standard errors are reported below each coefficient after adjustment for clustering at the product-level. ***, ** and * represent statistical significance at the 1%, 5% and 10% levels, respectively.

Table 11B: Antidumping Duties and the Probability of Product-Dropping
Matched Control Group 2

	Drop	Drop	Drop	Drop
Treatment*Post	-0.0383**	-0.0397***	-0.001	-0.003
	0.015	0.014	0.023	0.020
Post*Rate			-0.0028**	-0.0028**
			0.001	0.001
Product Shipments		-0.0766***		-0.0766***
		0.003		0.003
Product Tenure		-0.1257***		-0.1258***
		0.013		0.013
Year FE	Yes	Yes	Yes	Yes
Product FE	Yes	Yes	Yes	Yes
Observations	41,289	41,289	41,289	41,289
R-Squared	0.106	0.197	0.106	0.197

Notes: This table summarizes OLS regression coefficients of a binary variable indicating product-dropping (Drop) on the difference-in-difference interaction term "Treatment*Post" and the effective duty rate interaction term "Post*Rate." Robust standard errors are reported below each coefficient after adjustment for clustering at the product-level. ***, ** and * represent statistical significance at the 1%, 5% and 10% levels, respectively.

Table 12: Antidumping Duties and the Probability of Plant-Level Exit
Termination Control Group

	Exit	Exit	Exit	Exit
Treatment*Post	-0.0018	0.0169	-0.0024	0.0029
	0.0119	0.0137	0.0119	0.015
Post*Rate		-0.0013**		-0.0004
		0.0006		0.0007
No. Employees			-0.092***	-0.0919***
			0.0031	0.0031
Plant Age			-0.0022***	-0.0022***
			0.0004	0.0004
Capital Intensity			-0.0168***	-0.0168***
			0.0025	0.0025
Avg. Wage			-0.0746***	-0.0746***
			0.0077	0.0077
Multi-Unit			0.0934***	0.0934***
			0.0072	0.0072
Multi-Product			-0.0181***	-0.0181***
			0.0043	0.0043
Year FE	Yes	Yes	Yes	Yes
Product FE	Yes	Yes	Yes	Yes
Observations	62,285	62,285	62,285	62,285
R-Squared	0.059	0.059	0.116	0.116

Table 12A: Antidumping Duties and the Probability of Plant-Level Exit
Matched Control Group 1

	Exit	Exit	Exit	Exit
Treatment*Post	-0.0185	-0.0024	-0.0186	0.0034
	0.0145	0.0176	0.0139	0.0154
Post*Rate		-0.0012		-0.0017**
		0.0009		0.0007
No. Employees			-0.1018***	-0.1018***
			0.0055	0.0055
Plant Age			-0.0026***	-0.0026***
			0.0005	0.0005
Capital Intensity			-0.0147***	-0.0147***
			0.0027	0.0027
Avg. Wage			-0.0696***	-0.0697***
			0.0105	0.0105
Multi-Unit			0.0779***	0.0779***
			0.009	0.009
Multi-Product			-0.024***	-0.024***
			0.0051	0.0051
Year FE	Yes	Yes	Yes	Yes
Product FE	Yes	Yes	Yes	Yes
Observations	85,617	85,617	85,617	85,617
R-Squared	0.068	0.069	0.132	0.132

Table 12B: Antidumping Duties and the Probability of Plant-Level Exit
Matched Control Group 2

	Exit	Exit	Exit	Exit
Treatment*Post	-0.0038	0.0162	-0.0022	0.0038
	0.012	0.0135	0.012	0.0154
Post*Rate		-0.0014**		-0.0004
		0.0006		0.0007
No. Employees			-0.0926***	-0.0926***
			0.0032	0.0032
Plant Age			-0.0021***	-0.0021***
			0.0004	0.0004
Capital Intensity			-0.016***	-0.016***
			0.0027	0.0027
Avg. Wage			-0.0714***	-0.0715***
			0.0077	0.0077
Multi-Unit			0.0988***	0.0988***
			0.0077	0.0077
Multi-Product			-0.018***	-0.0179***
			0.0042	0.0042
Year FE	Yes	Yes	Yes	Yes
Product FE	Yes	Yes	Yes	Yes
Observations	53,741	53,741	53,741	53,741
R-Squared	0.046	0.046	0.102	0.102

Table 13: Relative Productivity of Product-Droppers

	TFP	LP
Drop	-0.0418***	-0.0830***
	0.0140	0.0143
Year FE	Yes	Yes
Product FE	Yes	Yes
Observations	44,382	44,382
R-Squared	0.684	0.371

Notes: This table summarizes OLS regression coefficients of revenue-based total factor productivity (TFP) and labor productivity (LP) on a binary variable indicating whether a plant dropped an investigated product. Robust standard errors are reported below each coefficient after adjustment for clustering at the product-level. ***, ** and * represent statistical significance at the 1%, 5% and 10% levels, respectively.

Table 14: Antidumping Duties and Output Rationalization

Year	Post	Treatment	Rationalization	Aggregate	Mean
1987	0	0	0.100	1.56	1.46
1992	0	0	0.075	1.53	1.45
1992	1	0	0.187	2.03	1.85
1997	1	0	0.171	1.81	1.64
1987	0	1	0.163	1.07	0.91
1992	0	1	0.176	1.33	1.15
1992	1	1	0.210	1.08	0.87
1997	1	1	0.166	1.15	0.98

Notes: This table reports a decomposition of revenue-based total factor productivity by year, post-treatment indicator (Post) and treatment status (Treatment). "Rationalization" is a term measuring the level of output rationalization, as described earlier. "Aggregate" is aggregate productivity. "Mean" is mean plant-level total factor productivity. "Treatment" equals 1 for plants that applied for and received protection and 0 for plants that applied for but did not receive protection. "Post" equals 1 for plants that had already been involved in an antidumping investigation in time t and 0 for plants that had not yet been involved in an investigation.

Table A.1 Results of Multinomial Logit and

Logit Models for Matched Control Groups[24]

	Matched Control Group 1		Matched Control Group 2
	Determinants of Protection Given Filing	Determinants of Termination Given Filing	Probability of Protection
Lagged Import Penetration	0.246***	-0.202	0.909***
	0.061	0.133	0.280
ln(Lagged Employment)	0.387***	0.326***	0.072
	0.059	0.058	0.091
ln(Labor Productivity)	0.210**	-0.355***	0.740***
	0.101	0.109	0.163
Real GDP Growth	0.044	0.003	0.024
	0.049	0.045	0.066
Price Growth	-0.053***	-0.017	-0.029*
	0.013	0.014	0.017
Number of Observations	3,423	3,423	619
Pseudo-R Squared	0.03	0.03	0.051
Estimation Technique	Multinomial Logit	Multinomial Logit	Logit

[24] Notes: This table summarizes estimation results for the multinomial logit and logit models used to generate the two matched control groups. In the multinomial logit model, the dependent variable takes a value of 1 if an industry never filed for protection, 2 if it filed but was turned down for protection and 3 if it applied for and received protection. In the logit model, the dependent variable takes a value of 1 if an industry applied for and received protection and 0 if it applied for, but did not receive protection. Independent variables are at the industry-year-level.

Chapter 2: Trade Liberalization, Productivity and Input Variety: Evidence from Colombian Plants

Section 1: Introduction

This paper identifies the determinants of productivity growth during a period of unilateral trade liberalization in Colombia. Importantly, this analysis is based on a comprehensive list of potential channels drawn from both the empirical and theoretical literatures on trade and productivity. After defining proxy variables representing each of the potential channels for productivity growth, I follow a two-stage empirical strategy. In the first stage, I examine how each of the channel proxy variables was affected by trade liberalization. In the second stage, I estimate the effect of changes in each channel's proxy variable on plant-level productivity.

This research builds on a substantial empirical literature, which has shown repeatedly that unilateral tariff reductions are productivity-augmenting in developing countries. In particular, Pavcnik (2002), Fernandes (2007) and Schor (2004) have shown that total factor productivity of manufacturers rose during periods of unilateral trade liberalization in Chile, Colombia and Brazil, respectively. It is now generally accepted that productivity and nominal tariffs are negatively correlated.

There is little understanding, however, of the forces driving the productivity growth experienced during trade liberalization. This paper expands on the existing literature by simultaneously examining the most important channels for productivity growth during trade liberalization and by measuring their relative contributions to changes in plant-level productivity

A. Background

Several papers have considered potential channels through which trade liberalization may affect within-plant productivity. Muendler (2004) was the first to examine multiple channels simultaneously, with a focus on the effect of trade liberalization on the elimination of so-called "x-inefficiencies" and on increased use of "higher-quality" foreign intermediate goods. Regressing productivity on measures of foreign competition including import penetration and nominal output tariffs, Muendler finds that higher levels of foreign competition—as measured by lower tariffs and higher import penetration—are associated with higher productivity. He cites this result as evidence that trade liberalization increases productivity through its impact on the elimination of x-inefficiencies. Regarding the effect of foreign intermediate inputs, Muendler notes that they are insignificant in his production function estimates and concludes that they are not important contributors to trade-driven productivity growth.

Fernandes (2007) also considers several potential channels for productivity growth during trade liberalization including total foreign input usage, investment in new equipment and skilled labor intensity. Fernandes finds that among the plants experiencing productivity gains, most increased their usage of foreign inputs, increased the skill-intensity of their workforce and invested more in new equipment. When regressing productivity on measures for each of these channels interacted with tariffs, she finds that productivity gains were larger for firms with higher foreign input usage and higher equipment investment.

Amiti and Konings (2007) and Schor (2004) focus primarily on the foreign input channel. Each hypothesizes that increased availability of foreign inputs may be one of the primary ways in which trade liberalization could increase plant-level productivity. To test this hypothesis, they regress productivity on input tariffs, as well as output tariffs. Each finds that input tariffs are important determinants of productivity growth. In fact, Amiti and Konings note that the effect of intermediate tariff reductions exceeds that of reductions in output tariffs.

These papers are valuable, in that they describe a number of potential channels through which trade liberalization may affect productivity. In this paper, I expand on that work in several ways. First, I consider a comprehensive list of potential channels drawn from the empirical and theoretical literatures on trade and productivity, incorporating new channels such as input variety and plant scale. Second, I provide a better understanding of the effect of the increased availability of foreign inputs on productivity by breaking down this effect into two channels—one focused solely on changes in the extensive margin of foreign input use[1] and one that is also affected by changes in the intensive margin.[2] Third, I explicitly consider the "x-inefficiency" effect often referred to as "trimming the fat," using a measure of industry structure that includes both domestic and foreign production. Lastly, I determine if the variables representing each of these channels were affected by trade liberalization, and if so, I assess whether the impact was in the expected direction. Ultimately, the set of channels I consider includes trade liberalization-driven changes in the intensity of foreign input usage, the extensive margin of foreign input usage, plant scale, technology adoption and industry structure.

B. Scope of the Analysis

It has long been acknowledged that trade liberalization can result in two types of productivity gains: increases in aggregate industry productivity and increases in within-plant productivity. Trade liberalization may yield gains in aggregate industry-level productivity when market share shifts from less productive to more productive firms, with the least productive firms reducing their output or being forced to exit. This output rationalization effect of trade liberalization has been demonstrated theoretically by Melitz (2002), Bernard, Eaton, Jensen and Kortum

[1] Expansion of the extensive margin of foreign input use refers to plants beginning to use foreign inputs in their production process, when those inputs had not been used in previous periods.

[2] Expansion of the intensive margin of foreign input use refers to plants that expand their usage of foreign inputs that had already been used in the production process in previous periods.

(2003) and affirmed empirically using data from a number of countries including Colombia, by Fernandes (2007).

In the case of Colombia, however, the impact of the output rationalization effect on productivity growth is dwarfed by within-plant productivity growth. Specifically, Fernandes found that 68 percent of total productivity gains during the trade liberalization period were caused by increases in within-plant productivity, rather than redistribution of market share. Moreover, there is no agreement in the empirical literature as to which channels are most important for within-plant productivity growth. This paper, therefore, concentrates solely on the determinants of changes in within-plant productivity, and takes as given the presence of the output rationalization effect.

C. Layout of Paper

Section II presents the set of channels considered in this analysis and describes the variables used to measure each channel. Section III describes the data and Section IV discusses changes in Colombian trade policy during the period covered in this study. Section V explains the empirical strategy in detail and presents the results. Section VI concludes.

Section 2: Channels For Productivity Growth

A. Extensive Margin of Foreign Input Usage

A number of researchers have suggested that trade liberalization may increase productivity by increasing the variety of inputs available to domestic firms. Ethier (1982) presents a two-sector framework, in which final goods producers with constant elasticity of substitution (CES) production functions experience productivity gains when trade liberalization expands the set of intermediate good varieties. A key aspect of this model is that productivity gains come exclusively through expansion along the extensive margin of input usage. That is, firms and plants experience productivity gains because they are able to use varieties of inputs that were not used prior to the trade liberalization.

While this extensive margin of intermediate input usage has been mentioned in empirical research by both Fernandes (2007) and Amiti and Konings (2007), neither of these papers addressed the issue directly. Fernandes provides statistics suggesting that among the set of plants experiencing productivity gains during liberalization, the majority increased the share of imported raw materials to output. Amiti and Konings, on the other hand, regressed plant-level productivity on intermediate input tariffs.

I examine expansion along the extensive margin of input usage by defining a binary variable that equals 1 if a plant uses foreign intermediate inputs and 0 otherwise. For a movement in this variable from 0 to 1 to truly represent an expansion along the extensive margin of input use, it must be case that foreign inputs are different varieties than their domestic equivalents, rather than simply another source for commodity-like raw materials. The data provide evidence for this conclusion. First, the extensive margin is based on use of foreign inputs, rather than foreign raw materials, which are tracked separately in the Colombian manufacturing dataset. Second, industries that have the highest share of plants using foreign intermediate inputs—Scientific Equipment, Electronic Machinery and Chemicals—are unlikely to use commodity-like raw materials.[3]

B. Increased Intensity of Foreign Input Usage

The increased availability of foreign inputs associated with trade liberalization can also increase productivity if foreign inputs are of a higher quality than those sourced domestically.[4] It may be, for example, that Colombian producers are implicitly importing R&D and skilled labor, through their imports of intermediate inputs. The key difference between this channel and the extensive margin channel described immediately above is that this quality effect can take place through expansion in the intensive margin of foreign input use. That is, plants will become more productive as they expand foreign input usage, even if those inputs were already being used—albeit less intensively—prior to the trade liberalization.

[3] In contrast, the industries that have the lowest share of plants using foreign intermediate inputs—Food, Clothing and Furniture—would be likely to use commodity-like raw materials.

[4] A number of authors have discussed this quality-based intensive margin channel, including Schor (2004), Amiti and Konings (2007) and Muendler (2004).

I measure the intensity of foreign input usage as the value share of foreign inputs in total input usage, although a clarification is required here. While the quality-based channel described above can operate only through the intensive margin, my proxy variable for this channel can be affected by changes in both the intensive and extensive margin. Therefore, this variable may reflect increases in the variety of intermediate inputs used, as well as increases in the intensity of inputs already used in the production process.

C. "Trimming the Fat"

Among the potential ways that trade liberalization can contribute to productivity growth, the most commonly mentioned in the literature is the reduction in x-inefficiency—sometimes referred to as trimming the fat—that occurs when domestic firms are faced with increased competition from abroad. At first glance, it might seem surprising that this channel would exist at all. If firms are profit-maximizing, they should already be taking the steps needed to minimize costs and maximize productivity prior to trade liberalization. There are, however, a number of reasons that trade liberalization may increase productivity through this competitive channel.

One of the most appealing arguments for the ability of trade liberalization to decrease x-inefficiency is proposed by Holmes and Schmidt (2001). Under this model, firms with monopoly power have an incentive to engage in unproductive rent-seeking behavior. Once trade liberalization reduces or eliminates their monopoly power, however, the incentive for the rent-seeking behavior disappears. Resources formerly dedicated to rent-seeking are then reallocated to productive activities, which generates an increase in productivity.[5]

I address this issue by considering how industry-level Herfindahl indexes were affected by trade liberalization, and in turn, how these changes in market structure were associated with productivity growth. If the story outlined in Holmes and Schmidt (2001) is correct, one would expect that productivity increases would be largest in those industries with the largest decreases in values of the Herfindahl index during liberalization. Calculation of each industry's Herfindahl index is discussed in detail in Section IV.

D. Increased Incentive to Invest in New Technology

As described by Goh (2000)—and noted by Amiti and Konings (2008) and Fernandes (2007)—trade liberalization may increase incentives to make productivity-augmenting investments. The mechanism for this incentive comes through the timing of the investment/production process. Under Goh's model, investment in a higher-productivity production process delays the time when the produced good can actually be sold. Since trade liberalization decreases current profit levels—i.e. decreases the opportunity cost of investing in higher-productivity

[5] In addition, Vousden and Campbell (1994) argue that trade liberalization may eliminate slack in firms with internal information asymmetries.

technology—it increases the incentive to invest.[6] I examine this channel by estimating the impact of tariff changes on investment in new equipment and machinery. The impact of new investment in machinery and equipment on within-plant productivity is then investigated.

E. Increases in Plant Scale

Increases in plant scale resulting from trade liberalization are an important source of productivity growth in theoretical models proposed by Ethier (1982) and Melitz (2003). An important distinction is that these increases in scale are driven in the theory by reciprocal tariff reductions by a country's trading partners in a move from autarky to free trade. This was not the case for Colombia, where all changes in policy were unilateral, rather than reciprocal. Nonetheless, due to the importance of scale to productivity, changes in plant scale are included in the analysis.

Section 3: Data

I employ a plant-level census of Colombian manufacturers covering the period from 1977 to 1991, collected by the *Departmento Administrativo Nacional de Estadistica* (DANE). This is the same dataset used in Fernandes (2007) and was generously provided by Mark Roberts. The dataset contains information on plant sales, raw material use, energy use, labor use, capital accumulation and investment.

[6] A number of authors including Rodrik (1992) and Crowley (2006) have argued that protection may have the opposite impact. That is, protection may increase the incentive to invest in new technology. I follow Fernandes (2007) in appealing to the arguments associated with a negative correlation between tariffs and investment.

It covers between 6,000 and 7,000 plants per year for a total of 100,170 observations. These data were used in estimation of industry-level production functions and calculation of plant-level productivity measures. Summary statistics are provided in Tables 1A-1D and 2A-2D.

Data on Colombian industry-level tariff rates were provided by Jorge Garcia-Garcia of the World Bank. These tariff rates are at the three-digit industry level, and correspond to the industries covered in the manufacturing census. The tariff rates imposed on an industry's output are relevant in determining, for example, how industry structure was impacted by trade liberalization.

When examining plants' decision of whether to import intermediate inputs, it is input tariffs that are the variable of interest. I calculate industry-level input tariffs as a weighted average of output tariffs. Weights are derived from the Colombian input-output table provided in the World Bank Trade and Production Database. Input tariffs are then calculated as follows

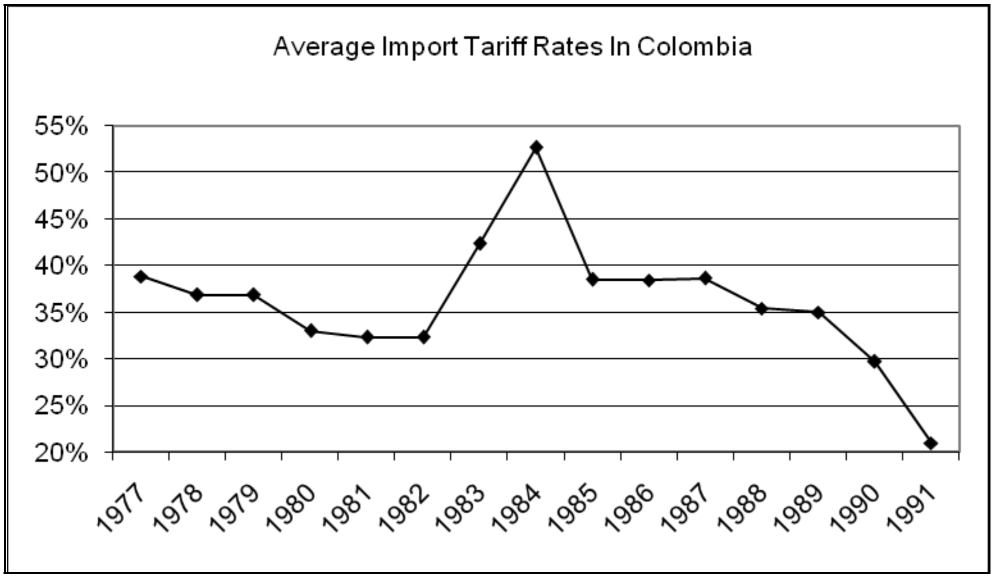
$$\tau_{it} = \sum_{j} s_j tar_{jt}$$

where τ_{it} is the calculated input tariff for industry i in time t, s_j is the share of each industry j in production of a unit of output in industry i and tar_{jt} is the output tariff in industry j at time t.

Note that the input share for each industry is time-invariant. This is due to the availability of input-output data for only a single year. While it would be preferable to have time-varying data on input shares, this data limitation seems relatively innocuous. While trade liberalization likely impacts the source country of inputs, it seems less likely that it would impact the sector allocation of inputs.

Section 4: Colombian Trade Policy

The period covered by the dataset—1977 to 1991—was characterized by significant fluctuations in tariff rates in Colombia. Colombia's trade policy during these 15 years can be separated into three distinct periods. In an initial liberalization period, from 1977 to 1982, the Colombian government unilaterally cut average tariff rates from 39 percent to 32 percent. The end of a coffee boom and subsequent recession in 1982 led to current account deficits and a return to protectionism. Average industry tariffs rose to 53 percent in 1984. Finally, a structural readjustment policy financed by international financial organizations led to a re-liberalization from 1984 to 1991, with average tariff rates dropping to almost 20 percent.



This period is particularly well-suited for examining the impact of changes in trade policy. Specifically, the unilateral nature of the changes in Colombian tariff rates allows me to isolate the effect of changes in a country's own tariff rates on productivity independently of reciprocal tariff reductions by other countries. This ensures that the measured changes in productivity are due to changes in the domestic market, rather than, for example, increased access to foreign markets.

Section 5: Empirical Strategy and Results

My analysis proceeds in three steps. In Step 1, I calculate three measures of plant-level productivity including production function residuals estimated using the technique of Levinsohn and Petrin (2003), a TFP index from Caves et al. (1982) and labor productivity. Step 2 involves estimating the impact of changes in tariff rates on each of the channels mentioned above. Lastly, in Step 3, I examine the impact of changes in each of the channel variables on plant-level productivity.

A. Step 1: Calculating Plant-Level Productivity Measures

1. Levinsohn & Petrin (2003) Production Function Residuals

Accurate measurement of TFP based on estimation of production functions is notoriously difficult. This difficulty is due to two potential types of error, which I will call methodological error and measurement error. Methodological error is the error associated with biased coefficients when production functions are inappropriately estimated using OLS. I adopt a procedure developed by Olley and Pakes (1996) and Levinsohn and Petrin (2003) to limit methodological error, which is discussed fully below. Measurement error is caused when the econometrician does not possess data on actual quantities of input and output usage and is forced to estimate production functions using deflated nominal values. I address this error by using the most detailed price indexes available, including industry-level price indexes for output, as well as input-specific price indexes that differentiate among raw materials, energy and the various types of capital.[7]

2. Estimating Production Functions

[7] Capital is separated into five sub-categories: land, buildings and structures, machinery and equipment, transportation equipment and office equipment. Price indexes that are specific to each type of capital are available from the Colombian Central Bank and were used to deflate each value.

Since plant-level total factor productivity measures will be based on a comparison of actual to predicted output levels, I begin by estimating a set of production functions. To allow for differences in input intensity and technology across industries, I estimate a separate production function for each industry, defined at the 3-digit SIC level.[8] The production functions are Cobb-Douglas with capital, labor, energy and raw materials as factors of production. Observations are at the plant level p, in industry i, at time t:

$$y_{pt}^{i} = \hat{\beta}_0 + \hat{\beta}_k^i k_{pt}^{i} + \hat{\beta}_l^i l_{pt}^{i} + \hat{\beta}_e^i e_{pt}^{i} + \hat{\beta}_m^i m_{pt}^{i} + \varepsilon_{pt}^{i} \tag{1}$$

$$\varepsilon_{pt}^{i} = \omega_{pt}^{i} + \mu_{pt}^{i} \tag{2}$$

where y_{pt}^{i} is total value of sales, as measured by total plant sales[9], k_{pt}^{i} is the perpetual inventory value of capital,[10] l_{pt}^{i} is total number of employees, e_{pt}^{i} is energy usage and m_{pt}^{i} is raw material usage, with all variables measured in logs.

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8 See Appendix 1 for a complete list of industries contained in the Colombian dataset.

9 Deflation techniques for each of the output and inputs variables are discussed in detail in Section c below.

10 Capital values are calculated using the perpetual inventory method. Under this method, capital in the initial year, 1977 is simply the total book value of capital provided by each plant. For successive years, capital is calculated by first depreciating the previous year's capital value with depreciation rates for each sub-category of capital from Pombo (1999). Current year investment rates are then added to this depreciated value to obtain the total capital value.

The error term is separated into two components. ω^i_{pt} represents a manager's knowledge of the plant's productivity, which is unknown to the econometrician. μ^i_{pt} on the other hand, represents a plant-specific productivity shock experienced at time t, which is not known to the plant or the econometrician.

a. Methodological Error

The presence of the ω^i_{pt} term creates a simultaneity bias when (1) is estimated using ordinary least squares. Suppose, as seems reasonable, that more productive firms purchase more raw materials and energy, hire more employees and invest in more capital, due to the higher profits associated with their higher plant-level productivity. In this case, OLS estimation of a production function will result in upwardly-biased input coefficients.

The key to eliminating this simultaneity bias is to use available information to identify the plant-specific productivity term ω^i_{pt}. Suppose we represent demand for raw materials, m^i_{pt} as a function of the state variables k^i_{pt} and ω^i_{pt}:

(3) $$m^i_{pt} = m^i_{pt}(k^i_{pt}, \omega^i_{pt})$$

It seems relatively innocuous to assume that $m^i_{pt}(.,.)$ is strictly monotone in each of its arguments. That is, the higher the level of capital or plant-specific productivity, the higher will be that plant's demand for raw materials.

It is then possible to invert (3) to represent plant-specific productivity in terms of capital and raw material usage:

(4) $$\omega^i_{pt} = \omega^i_{pt}(k^i_{pt}, m^i_{pt})$$

Then, following Olley and Pakes (1996) and Levinsohn and Petrin (2003) I assume that productivity follows a first-order Markov process:

(5) $$\omega^i_{pt} = E[\omega^i_{pt} \mid \omega^i_{pt-1}] + \xi_t$$

I implement the assumptions contained in equations (3) - (5) in order to obtain consistent coefficients for each factor of production. To do this, I first rewrite (1) to include the plant-specific productivity term ω^i_{pt}:

(6) $$y^i_{pt} = \beta^i_l l^i_{pt} + \beta^i_e e^i_{pt} + \beta^i_k k^i_{pt} + \beta^i_m m^i_{pt} + \omega^i_{pt} + \eta^i_{pt}$$

which is then rewritten as follows:

(7) $$y^i_{pt} = \beta^i_l l^i_{pt} + \beta^i_e e^i_{pt} + \phi^i_{pt}(k^i_{pt}, m^i_{pt}) + \eta^i_{pt}$$

where

(8) $$\phi^i_{pt}(k^i_{pt}, m^i_{pt}) = \beta^i_0 + \beta^i_k k^i_{pt} + \beta^i_m m^i_{pt} + \omega^i_{pt}(k^i_{pt}, m^i_{pt})$$

I then express (8) as a third-order polynomial approximation in k^i_{pt} and m^i_{pt}

(9) $$\phi^i_{pt}(k^i_{pt}, m^i_{pt}) = \sum_{i=0}^{3}\sum_{j=0}^{3-i} \delta_{ij} k^i_t m^j_t$$

and substitute (8) into (7) to obtain

(10) $$y^i_{pt} = \delta^i_o + \beta^i_l l^i_{pt} + \beta^i_e e^i_{pt} + \sum_{i=0}^{3}\sum_{j=0}^{3-i}\delta_{ij} k^i_t m^j_t + \omega^i_{pt} + \eta^i_{pt}$$

which is then estimated by OLS.[11] This process provides consistent estimates of the coefficients β^i_l and β^i_e as well as the component coefficients of $\phi_t(.,.)$.

Next I turn to identifying the coefficients β^i_k and β^i_m. To do so, I first define $\hat{\phi}_t$ using the fitted values and coefficient estimates from equation (10):

(11) $$\hat{\phi}_t = \hat{y}^i_{pt} - \hat{\beta}^i_l l^i_{pt} - \hat{\beta}^i_e e^i_{pt}$$

I next estimate $\hat{\omega}_t$ as

(12) $$\hat{\omega}^i_{pt} = \hat{\phi}^i_{pt} - \beta^*_k k^i_{pt} - \beta^*_m m^i_{pt}$$

for any candidate values β^*_k and β^*_m. Using these values, I can derive a consistent approximation of $E[\omega_t \mid \omega_{t-1}]$ based on the following regression:

(13) $$\hat{\omega}^i_{pt} = \gamma^i_0 + \gamma^i_1 \omega^i_{t-1} + \gamma^i_2 \omega^{2i}_{t-1} + \gamma^i_3 \omega^{3i}_{t-1} + \varsigma^i_t$$

The fitted values from this regression then become $\hat{E}[\omega_t \mid \omega_{t-1}]$. Using these components, I can derive a residual term for any pair (β^*_k, β^*_m):

(14) $$\hat{\eta}^i_{pt} + \hat{\xi}^i_{pt} = y^i_{pt} - \hat{\beta}^i_l l^i_{pt} - \hat{\beta}^i_e e^i_{pt} - \beta^{*i}_k k^i_{pt} - \beta^{*i}_m m^i_{pt} - \hat{E}[\omega_t \mid \omega_{t-1}]$$

Since this residual must be interacted with at least two instruments, I follow Levinson and Petrin (2003) in employing the following moment conditions:

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[11] Notice that β^i_0 is not separately identified from the intercept of $\phi_t(.,.)$.

(15) $E[\eta^i_{pt} + \xi^i_{pt} \mid k^i_{pt}] = 0$

(16) $E[\eta^i_{pt} + \xi^i_{pt} \mid m^i_{pt-1}] = 0$

Then, with my instruments defined as $Z^i_t \equiv (k^i_t, m^i_{t-1})$ my estimates of β^i_k and β^i_m solve

(17) $\min_{\beta^*_k, \beta^*_m} \sum_h [\sum_t (\hat{\eta}^i_{pt} + \hat{\xi}^i_{pt}) Z_{ht}]^2$

Newton's method is used to find the vales of β^*_k and β^*_m that minimize (17). This procedure returns consistent estimates of all input coefficients in the production function.

b. Measurement Error

While measurement of "true" productivity requires—at a minimum—information on the quantities of output and inputs, these data are recorded in the Colombian dataset in nominal terms. Without plant-specific pricing data, it is impossible to perfectly separate changes in quantities from changes in mark-ups.

I use the most specific price indexes available to deflate plant-level sales and obtain a measure of output for use in estimating production functions. Specifically, I employ price indexes at the 3-digit SIC level produced by the Central Bank of Colombia and provided by Jorge Garcia-Garcia of the World Bank. Using industry-level price indexes to deflate sales controls for variation in mark-up changes across industries experiencing different degrees of trade liberalization. This technique is not perfect, since it is unable to account for heterogeneity in plant-level mark-ups within industries. However, provided that changes in mark-ups caused by variation in tariff rates are relatively uniform within each industry, it is effective at separating mark-up effects from true productivity effects.

It is also necessary to deflate the inputs used to estimate production functions. I deflate capital using price indexes from the Colombian Central Bank. Importantly, these price indexes are specific to each of the sub-types of capital tracked in the manufacturing census: buildings, machinery and equipment, transportation equipment and office equipment. To deflate land, raw materials and energy, I use the Colombian PPI as reported in the IMF's *International Financial Statistics*. The labor term in the production function is measured using total number of employees, so no deflation is necessary.

3. Calculating Plant-Level Productivity Measure

a. Levinsohn and Petrin Semi-Parametric Estimator

The preceding two sections discussed the measures taken to ensure the consistency of coefficient estimates in production functions and to minimize the measurement error associated with observing only nominal values. I incorporate these steps when estimating the production functions used to calculate the plant-level productivity measures.

Once I have estimated input coefficients as described above, productivity is defined simply as the difference between each plant's actual output and its fitted value based on its industry-specific production function:

(18) $prod_{pt}^{i} = y_{pt}^{i} - \hat{\beta}_{k}^{i} k_{pt}^{i} - \hat{\beta}_{l}^{i} l_{pt}^{i} - \hat{\beta}_{e}^{i} e_{pt}^{i} - \hat{\beta}_{m}^{i} m_{pt}^{i}$

These plant-level productivity measures become the dependent variable in regressions examining the effect of each of the channels considered in this paper.

Summary statistics showing variation in the Levinsohn and Petrin (2003) productivity measure across years and industries are reported in Tables 1A, 1B, 2A and 2B.

b. Caves et al. TFP Index

Most recent empirical papers in the literature on trade and productivity have measured TFP using some variant of the Olley and Pakes (1996) or Levinsohn and Petrin (2003) procedures. As described above, however, the strict structural assumptions involved in estimating the Levinsohn and Petrin (2003) productivity measures make a robustness check desirable. To this end, I calculate plant-level productivity measures based on the index method developed in Caves et al. (1982).

This TFP index has several desirable properties. First, it is based on observed values of output and inputs, rather than estimated production function parameters. Second, as in the Levinsohn and Petrin (2003) method, the TFP measures are comparable across different industries and years. Lastly, while it is based on observed values, the TFP index is still able to capture substitution between different inputs in a way that single-factor productivity measures are not.

Following Aw, Chen and Roberts (2001) I construct a TFP index for each plant *p* in year *t* using the set of inputs *m*={Capital, Labor, Energy, Raw Materials}. Let X^{i}_{mpt} be the expenditure of plant p in time t on input m and S^{i}_{mpt} be the share of input m in total revenue. I calculate average input usage and shares at the industry-year level to be consistent with the estimation of industry-level production functions in the Levinsohn and Petrin (2003) approach described above. Therefore, $\overline{S}^{i}_{mt}$, $\ln \overline{Y}^{i}_{t}$ and $\overline{X}^{i}_{mt}$ are the arithmetic means of industry-level input shares, revenue and input expenditure. The plant-level productivity measure is then calculated as follows:

$$(19)\quad \ln TFP^{i}_{pt} = (\ln Y^{i}_{pt} - \ln \overline{Y}^{i}_{t}) + \sum_{s=2}^{t} (\ln \overline{Y}^{i}_{t} - \ln \overline{Y}^{i}_{t-1})$$

$$-[\sum_{m} \frac{1}{2}(S^{i}_{mpt} + \overline{S}^{i}_{mt})(\ln X^{i}_{mpt} - \ln \overline{X}^{i}_{mt})$$

$$+\sum_{s=2}^{t} \sum_{m} \frac{1}{2}(\overline{S}^{i}_{mt} + \overline{S}^{i}_{mt-1})(\ln \overline{X}^{i}_{mt} - \ln \overline{X}^{i}_{mt-1})]$$

As described in Aw, Chen and Roberts (2001), this TFP expression measures the performance of each plant, relative to a hypothetical plant producing the mean level of output with the mean level of inputs in the base period, 1977. The TFP index therefore incorporates a plant's deviation of output and inputs from the industry mean in any given year, but also from the mean in the base period. This calculation yields a TFP measure that is comparable across plants and years. Summary statistics showing variation in the TFP index across years and industries are reported in Tables 1A, 1B, 2A and 2B.

c. Labor Productivity

While single-factor productivity measures such as labor productivity are computationally simple, they are useful to use in robustness checks of results based on the more complex measures of multi-factor productivity described above. I calculate labor productivity simply as the ratio of total revenue—deflated using industry-level price indexes—to the total number of employees at the plant level. Summary statistics showing variation in labor productivity across years and industries are reported in Tables 1A, 1B, 2A and 2B.

B. Step 2: Estimating The Effect of Trade Liberalization on Channels

My ultimate goal is to identify the channels through which trade liberalization affected plant-level productivity. But before examining the effect of the identified channels—foreign input extensive margin, foreign input intensive margin, technology adoption, trimming the fat and scale—on productivity, it is first necessary to determine whether each of these channels was affected by the process of trade liberalization. To obtain a more thorough understanding of the determinants of variation in the channel proxy variables, I specify comprehensive models based on the theoretical and empirical literatures related to each of the channels. Results from estimation of these models are presented in Tables 3 through 7.

1. The Effect of Trade Liberalization on The Extensive Margin of Foreign Input Use

It seems natural, *a priori*, to expect that lower tariff rates would result in a higher probability of a plant expanding its extensive margin of foreign input use. To rigorously examine this question, however, I consider a more complete picture of the variables affecting a firm's decision of whether to import intermediate inputs. While there is not a well-developed literature examining the plant-level characteristics that may be involved in the decision of whether to import foreign intermediates, the literature on entry into the export market provides useful parallels. For example, fixed costs associated with identifying overseas customers and suppliers and conducting transactions in foreign currencies would be incurred by both exporters and importers. Similarly, it is likely that plant-level characteristics related to workforce sophistication may affect the decision of whether to import foreign intermediate inputs, as it would affect the export entry decision.

Recognizing these similarities between export and import decisions, I employ a static version of the dynamic binary choice model in Bernard and Wagner (2001). That is, I estimate the following:

(20) $Y_{it} = 1$ if $\beta X_{it} + u_{it} > 0$

= 0 otherwise

Here, Y_{it} is a binary variable equal to one if the plant imported foreign intermediate inputs in period t. X_{it} is a set of plant-level variables that may affect the decision of whether to import foreign intermediate inputs including the share of skilled labor in total labor, average wage and plant scale. Skilled labor share and average wage are included as measures of workforce quality. If imported intermediate inputs are of a higher quality than domestically sourced inputs, a higher-quality workforce may be associated with importing intermediate inputs. Furthermore, if only the largest firms are able to overcome the fixed costs associated with importing intermediates, scale may be a factor in the import decision. Lastly, I will examine how the probability of importing foreign inputs responds to changes in input and output tariff rates—the primary variables of interest.

Results are presented in Table 3. I find that a 10 percent decrease in input tariffs is associated with a 7 percent increase in the probability of importing foreign intermediates. Lower output tariffs are also associated with a higher probability of using foreign inputs, although the magnitude of the coefficient—in absolute value—is lower. This lower magnitude for output tariffs is to be expected, since it is tariffs on intermediate inputs—rather than tariffs on output—that should be the determinants of the decision to import intermediate inputs.

Other independent variables also have the expected effect on the probability of importing intermediate inputs. Larger plants are more likely to import inputs, consistent with the idea that they are better able to incur the fixed costs associated with sourcing inputs from overseas. Similarly, the measures of workforce quality—average wage and share of skilled labor in total employment—are also associated with an increased probability of using foreign intermediate inputs.

2. The Effect of Trade Liberalization on Technology Adoption

As discussed above, there is theoretical evidence that trade liberalization can increase the incentive for plants to invest in new technology. While there is no perfect measure of technology adoption, reasonable proxies are present in the manufacturing census dataset. I measure technology adoption as the share of new investment in machinery and equipment in output. I do not include investment in used machinery or self-produced machinery in the construction of this variable, because these types of investment would not represent adoption of new higher-technology equipment.

To measure the effect of trade liberalization on the technology adoption variable, I again specify a comprehensive model considering variables that may affect a plant's investment in new technology. For this exercise it seems reasonable to use the same set of variables used to examine plants' foreign import decision. As in importing foreign inputs, purchases of new technology will likely be dependent on the size of the plant, as well as the skill-intensity and overall sophistication of its workforce. Therefore, I estimate the following equation with plant and year fixed effects:

(21)

$$NewInv_{pt}^{i} = \hat{\beta}_0 + \hat{\beta}_1 Tariff_{it} + \hat{\beta}_2 Scale_{pt}^{i} + \hat{\beta}_3{}^{i}_{pt} AvgWage + \hat{\beta}_4 SkilEmp_{pt}^{i} + \mu_t + \gamma_p + e_{pt}$$

where *NewInv* is the share of investment in new equipment and machinery in total revenue, *Tariff* is the industry-level tariff rate, *Scale* is plant-level scale measured in total employment, *AvgWage* is the plant-level average wage and *SkilEmp* is the plant-level share of skilled employees in total employment. Results are reported in Table 4.

I find that lower input tariffs are associated with higher investment in new equipment and machinery. Specifically, a ten percent decrease in input tariff rates is associated with slightly more than a one percent increase in the share of investment in new equipment and machinery. Changes in output tariff rates had no effect on investment in new machinery and equipment.

3. The Effect of Trade Liberalization on Industry Structure ("Trimming the Fat")

In the empirical literature on trade protection and productivity, many empirical researchers have identified "trimming the fat" as an important channel for productivity growth during trade liberalization. According to this story, the increased competition arising from trade liberalization forces plants to eliminate "x-inefficiencies" that had arisen as a result of protection. Due to the nebulous nature of this channel, however, it has remained an often-discussed, but seldom-studied phenomenon. This need not be the case.

The most plausible theoretical argument for the "trimming the fat" effect is based on the elimination of rent-seeking activities when a plant with monopoly power under protection loses this power to foreign competitors when tariffs fall. It is natural, therefore, to track the importance of this channel by examining the impact of trade liberalization on an industry's Herfindahl index and, in turn, the impact of that change in market structure on plant-level productivity.

Fernandes (2007) noted that trade liberalization had the largest effect on plant-level TFP in the least competitive industries, as measured by Herfindahl indexes and turnover rates. The Herfindahl indexes used in this analysis, however, were based only on domestic production and therefore do not take into account the impact of foreign competitors on industry structure, either before or after the trade liberalization. On the other hand, Muendler (2004) analyzes the "trimming the fat" channel by considering only measures of foreign competition, namely tariff rates and import penetration. However, the introduction of foreign competition may not have as large an effect if the domestic industry is already highly competitive.

I supplement the domestic production database with industry-level import data to construct a Herfindahl index that is inclusive of both domestic and foreign production. Naturally, since there is no plant-level data available for foreign producers, this calculation relies on a simplifying assumption. Specifically, in calculating this international Herfindahl index, I treat imports from each country as an individual plant. It is, of course, unlikely that foreign production from a particular country is produced at a single plant, but this assumption at least allows for creation of a Herfindahl index that incorporates the response of foreign producers to Colombia's trade liberalization.

In examining the effect of trade liberalization on the calculated Herfindahl index, I employ a comprehensive list of potential determinants of industry concentration considered in Ratnayake (1999). These determinants include traditional domestic variables likely to impact industry concentration such as advertising intensity (*AI*), industry size (*SIZE*), minimum efficient scale of plants (*MES*)[12] and capital intensity (*KI*) and tariff rates (*TARIFF*). I am unable to reproduce the foreign ownership variable included in Ratnayake (1999) because this information is not available in the Colombian dataset.

[12] I adopt the definition of minimum efficient scale from Baldwin and Gorecki (1985, 1986): minimum efficient scale is the average size of the largest plants accounting for the top 50 percent of industry size.

I estimate the effect of each of these variables on industry concentration with industry and year fixed effects:

(22)

$$HERF_{it} = \hat{\beta}_0 + \hat{\beta}_1 TARIFF_{it} + \hat{\beta}_2 AI_{it} + \hat{\beta}_3 SIZE_{it} + \hat{\beta}_4 MES_{it} + \hat{\beta}_5 KY_{it} + \mu_t + \gamma_i + e_{it}$$

There is a risk, however, of reverse causality in the relationship between tariff rates and industry concentration. Specifically, it may be the case that more concentrated industries are better able to overcome any free-rider problems associated with lobbying efforts and are therefore more effective at seeking tariff protection. I address this concern in two ways. First, I re-estimate the equation above with lagged tariffs, $TARIFF_{it-1}$. Provided that current Herfindahl levels do not affect last period's tariff rates, this will help mitigate potential endogeneity. Second, I employ the GMM procedure developed by Arellano and Bond (1991), which uses lagged values of the independent and dependent variables to construct internal instruments to address endogeneity. Results are reported in Table 5.

The Herfindahl index is unaffected by changes in nominal tariff rates. I do find, however, that higher import penetration is associated with a lower Herfindahl index, indicating that trade liberalization may be associated with lower industry concentration, to the extent that trade liberalization increases import penetration. Export intensity and industry concentration are also negatively related, indicating that increased trade in either the exporting or importing direction is associated with lower industry concentration. In addition, industries with larger minimum efficient scales are more concentrated, as expected, and larger industry sizes are associated with lower Herfindahl indexes.

4. The Effect of Trade Liberalization on Plant Scale

Scale is often considered to be one of the most important determinants of plant-level productivity. Furthermore, it is often thought that scale and TFP are positively related, demonstrating the existence of some level of increasing returns to scale. If trade liberalization increases the scale of domestic producers, as suggested in models by Ethier (1982) and Melitz (2002), then changes in scale provide another channel for productivity growth.

A number of authors have considered the impact of foreign competition—measured either through import penetration or tariff rates—on plant scale.[13] I base my analysis on Baldwin and Gorecki (1986), who estimate the impact of a comprehensive set of variables on relative plant scale in Canada and the United States. Baldwin and Gorecki conducted their analysis on two cross-sections, exploiting variation across industries. I conduct the analysis on the full panel to also exploit variation across time. Specifically, I estimate the following equation with plant and time fixed effects:

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[13] See Tybout (2001) for a brief survey of this literature.

(23)

$$SCALE_{pt} = \hat{\beta}_0 + \hat{\beta}_1 IP_{it} + \hat{\beta}_2 MESMSD_{it} + \hat{\beta}_3 EASTV_{pt} + \hat{\beta}_4 CDR_{pt} + \hat{\beta}_5 Tariff_{it} + \mu_t + \gamma_p + e_{pt}$$

where *IP* is the import penetration rate in 1978,[14] *MESMSD* is the ratio of market size to the output of the minimum efficient scale-plant,[15] *CDR* is a measure of the "cost disadvantage ratio" between large and small plants[16] and *EASTV*, which is the ratio of market share to minimum efficient scale when both tariff protection and concentration are greater than their respective means and zero otherwise. Results are reported in Table 6.

Trade liberalization, in the form of lower output tariff rates does not have a statistically significant impact on average plant scale. A higher cost penalty for firms operating below minimum efficient scale, as measured by *CDR* is associated with higher plant size, as one would expect. Similarly, MESMSD takes the expected negative sign, driven by the impact of higher minimum efficient scale in the denominator. In contrast, higher import penetration is associated with lower plant size.

[14] Import penetration in 1978—the first year for which trade data are available—is used to control for an industry's initial exposure to trade. Importantly, initial import penetration is uncorrelated with future changes in tariff rates.

[15] Minimum efficient scale is defined as the average size of the smallest number of the largest plants accounting for the top 50 percent of industry size as in Baldwin and Gorecki (1985, 1986).

[16] CDR is the ratio of the average size of the largest plants producing 50 percent of an industry's output to the average size of the smallest plants producing 50 percent of the industry's output.

5. The Effect of Trade Liberalization on the Intensity of Foreign Input Usage

Muendler (2004), Schor (2004) and Amiti and Konings (2007) have argued that productivity may increase following a trade liberalization because firms are able to use higher-quality foreign inputs more intensively. I examine the effects of trade liberalization on the intensity of foreign input usage using the same set of control variables employed to consider the extensive margin channel:

(24)

$$ForShare^{i}_{pt} = \hat{\beta}_0 + \hat{\beta}_1 Tariff_{it} + \hat{\beta}_2 Scale^{i}_{pt} + \hat{\beta}_3 {}^{i}_{pt} AvgWage + \hat{\beta}_4 SkilEmp^{i}_{pt} + \mu_t + \gamma_p + e_{pt}$$

where *ForShare* is the share of foreign intermediate inputs in total input usage and the control variables are the same as described above. Results are reported in Table 7.

The share of foreign inputs in a plant's production process is unaffected by changes in tariff rates. It appears that while trade liberalization does increase the probability of using foreign intermediate inputs—as described above—it does not affect the intensity of their usage in the production process.

C. Step 3: The Effect of Channel Variables on Productivity

1. Empirical Strategy

Step 2 provided useful information toward the goal of identifying which channels were drivers of productivity growth during Colombia's unilateral trade liberalization. Importantly, I found that three potential channels—the intensive margin of foreign input usage, the "trimming the fat" effect measured by industry concentration and changes in plant scale—were unaffected by changes in tariff rates. As a result, these channels will be excluded from the specification of interest, which will estimate the effect of tariff-responsive channels on productivity.[17]

The exclusion of foreign input intensity, industry concentration and plant scale from Step 3 is not meant to suggest that these variables are not determinants of plant-level productivity growth. Rather, it is meant to acknowledge that they are unaffected by changes in tariff rates and, therefore, cannot be sources of the productivity growth specifically associated with trade liberalization. In Step 3, therefore, my attention will focus on the channel variables that were found to be responsive to tariff changes—the extensive margin of foreign input usage and investment in new machinery and equipment.[18]

To examine the effect of changes in these "responsive" channels on productivity growth, I regress each of the three plant-level productivity measures described above on the relevant proxy variables. That is, I estimate the following equation with year, industry and plant fixed effects:

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[17] There is an additional reason to exclude plant scale from the equation estimated in Step 3. When estimating production functions as part of process of calculating Levinsohn and Petrin TFP, the results indicated a failure to reject the null hypothesis of constant returns to scale in 22 of 26 industries.

[18] Nonetheless, the additional channel variables that were found to be unaffected by changes in tariff rates will be considered in robustness checks discussed below.

$$(25) \quad prod_{pt} = \hat{\beta}_0 + \hat{\beta}_1 \, Extensive_{pt} + \hat{\beta}_2 \, NewTech_{pt} + \mu_t + \lambda_i + \gamma_p + e_{pt}$$

where *prod* is measured productivity, *Extensive* is a binary variable, which takes the value of one if the plant uses foreign intermediate inputs and *NewTech* is the share of investment in new machinery and equipment in total revenue. Results are reported in column 1 of Table 8A (labor productivity), Table 8B (Levinsohn and Petrin TFP) and 8C (TFP Index). In addition, as a first step toward controlling for endogeneity and possible dynamics in productivity, I re-estimate equation (25) in first differences using the GMM procedure developed by Arellano and Bond (1991). Results of this specification are reported in column 2 of Tables 8A, 8B and 8C.

2. Results: Extensive Margin of Foreign Input Usage

An expansion of the extensive margin of foreign input usage is associated with an increase in productivity, although this result is somewhat sensitive to the productivity measure employed. Specifically, the extensive margin binary variable is associated with an increase in productivity in the fixed effects and GMM specifications for labor productivity (Table 8A). This result is also found with the Levinsohn and Petrin (Table 8B) productivity measure, although there is no extensive margin effect in the Arellano and Bond specification. TFP as measured by the Caves, Christensen and Diewert (1982) index number was unaffected by changes in the extensive margin.

This result, combined with those of Step 2, indicates that trade liberalization is productivity-augmenting, in part, because it expands the extensive margin of foreign input usage, which in turn increases productivity. Importantly, this effect is distinct from any increase in the share of foreign inputs in total input usage. While trade liberalization increased the probability of plants moving from non-importers to importers of foreign inputs, reduced tariffs had no effect on the intensity of foreign input usage among plants that were already importing inputs.

3. Results: New Investment in Technology

Increased investment in new technology is associated with a reduction in same-period total factor productivity. At first glance, this result—where investment in new machinery is associated with lower productivity—appears surprising. One potential explanation for this result, however, is that it takes time for productivity gains from new equipment to materialize. In the interim period, when employees are still learning to use the new equipment and management has not yet determined how to integrate the equipment into the production process most effectively, it may be the case that productivity growth slows.

I address this potential explanation of the negative coefficient on new machinery investment by including lagged values of that variable from one to four years. Results are reported in columns 3 and 4 of Tables 8A-8C. The labor productivity results in Table 8A support the explanation provided above.

Specifically, current year productivity remains negatively affected investment in new technology, the results presented in columns 3 and 4 indicate that investment in new technology occurring in period t-4 had a positive effect on productivity in period t. It should be noted, however, that the analogous results for Levinsohn and Petrin TFP and the TFP index do not support this story, as the coefficient for both current and lagged investment in new machinery is negative.

In sum, evidence on the effect of investment in new machinery and equipment on productivity appears weak. While Step 2 showed that trade liberalization tended to increase investment in new machinery, therefore, it does not appear that this new investment had a significant impact on plant-level productivity growth. As a result, I am unable to conclude that investment in new machinery was an important channel for the productivity-augmenting effects of trade liberalization.

4. Robustness Checks

The results of a number of robustness checks are reported in columns 5-12 of Tables 8A, 8B and 8C. The first robustness check adds output and input tariffs to equation (25). As seen in columns 5 and 6, inclusion of these two tariff variables does not change results for the variables of interest—input extensive margin and investment in new machinery.

Columns 7-12 add the additional channel variables that were not initially included in equation (25) because they were found to be unresponsive to changes in tariff rates in Step 2. Columns 7 and 8 include the industry-level Herfindahl index, which was found to be responsive to changes in import penetration, but not to tariff rates. The effects of input extensive margin and investment in new machinery on productivity remain the same as in columns 1 and 2 for each productivity measure. Higher values of the Herfindahl index are associated with lower plant-level productivity for all productivity measures. This is the expected result, which indicates that plants in less concentrated, more competitive industries tend to have higher productivity growth than those in highly concentrated industries. As mentioned above, this indicates that while industry concentration may be an important determinant of productivity growth, it is not a source of the productivity growth associated specifically with trade liberalization.

The share of foreign inputs in total input usage is added in columns 9 and 10 to capture the intensive-margin effect of foreign inputs described above. Higher shares of foreign inputs are associated with an increase in productivity in both labor productivity specifications and the fixed effects specification of the TFP index. This relationship provides some evidence for the existence of a positive effect of more intensive foreign input usage on productivity, although this relationship was not affected by Colombian trade policy. As with the addition of the Herfindahl index variable, the inclusion of foreign input share did not change the results for the variables of interest.

Section 6: Conclusion

While there is extensive evidence that trade liberalization is productivity-augmenting in developing countries, there has been relatively little understanding of the forces driving this growth. This paper examined the determinants of plant-level productivity growth during Colombia's unilateral trade liberalization, which took place from 1977 to 1991. I began by examining five potential channels through which trade liberalization may have affected productivity growth in Colombia. These five channels included the extensive margin of foreign input usage, the intensity of foreign input usage, plant scale, technology adoption and the competitive channel often described as "trimming the fat."

Next, I examined the responsiveness of the proxy variables representing each of these channels to trade liberalization. I found that trade liberalization was associated with expansion of the extensive margin of foreign input use and increased investment in new equipment and machinery. In contrast, the intensity of foreign input usage, industry concentration (the "trimming the fat" effect) and plant scale were unaffected by Colombian trade policy. These three channels were therefore ruled out as sources of the productivity growth associated with trade liberalization, although they may be important determinants of productivity growth in general.

Finally, I examined the effect of changes in the proxy variables for foreign input extensive margin and investment in new machinery and equipment on three different measures of plant-level productivity. The results showed that expansion of the extensive margin of foreign input usage was associated with higher productivity. Increases in investment in new machinery and equipment, however, did not have a clear effect on productivity growth.

Table 1A: Summary Statistics by Year; All Products; Productivity Measures and Channels

	Productivity Measures		
Year	L&P TFP (Log)	Index TFP (Log)	Labor Prod. (Log)
1977	5.056	-0.089	13.09
1978	5.128	-0.086	13.19
1979	5.172	-0.054	13.19
1980	5.140	-0.072	13.16
1981	5.094	-0.092	13.15
1982	5.070	-0.085	13.14
1983	5.097	-0.088	13.23
1984	5.081	-0.078	13.32
1985	5.115	-0.030	13.35
1986	5.102	0.002	13.39
1987	5.080	0.037	13.41
1988	5.091	0.056	13.52
1989	5.067	0.060	13.54
1990	5.082	0.092	13.59
1991	5.043	0.062	13.60
Units	Index	Index	Employees/Unit of Output (Real Pesos)

Note: Table 1A continued on next page.

Table 1A: Summary Statistics by Year; All Products; Productivity Measures and Channels (Cont.)

Determinants of Productivity Changes (Channels)									
Year	Tariffs	Intermediate Tariffs	Tot. Revenue (Log)	Foreign Input Dummy	Foreign Input Share	Foreign Raw Material Dummy	Foreign Raw Material Share	Share of Machinery and Investment	Herf Index
1977	43.5	30.6	16.537	N/A	N/A	0.299	0.113	0.138	0.045
1978	42.3	28.5	16.669	N/A	N/A	0.301	0.114	0.156	0.042
1979	42.3	28.5	16.666	N/A	N/A	0.289	0.110	0.158	0.040
1980	39.4	25.9	16.613	N/A	N/A	0.289	0.107	0.167	0.041
1981	38.8	24.7	16.590	0.210	0.083	0.285	0.105	0.181	0.044
1982	39.2	24.9	16.525	0.185	0.071	0.257	0.097	0.187	0.044
1983	52.0	33.2	16.805	0.209	0.079	0.277	0.104	0.174	0.046
1984	64.8	41.3	16.878	0.204	0.077	0.272	0.105	0.153	0.047
1985	45.0	31.8	16.861	0.201	0.079	0.267	0.102	0.120	0.051
1986	44.9	31.6	16.887	0.194	0.075	0.251	0.097	0.111	0.050
1987	45.6	31.1	16.902	0.188	0.072	0.243	0.095	0.109	0.051
1988	42.0	29.1	16.946	0.187	0.070	0.240	0.092	0.105	0.057
1989	41.2	28.0	16.924	0.180	0.067	0.232	0.089	0.109	0.063
1990	34.1	24.9	16.967	0.176	0.065	0.227	0.085	0.093	0.069
1991	24.7	18.3	16.975	0.184	0.065	0.233	0.085	0.333	0.077
Units	Percent	Percent	Real Pesos	Binary	Percent	Binary	Percent	Percent	Index

Table 1B: Summary Statistics by Year; Final Goods; Productivity Measures and Channels

	Productivity Measures		
Year	L&P TFP (Log)	Index TFP (Log)	Labor Prod. (Log)
1977	5.148	-0.080	12.904
1978	5.219	-0.099	12.981
1979	5.244	-0.065	12.987
1980	5.232	-0.072	12.957
1981	5.170	-0.095	12.944
1982	5.139	-0.094	12.915
1983	5.219	-0.091	12.973
1984	5.220	-0.061	13.082
1985	5.236	-0.020	13.089
1986	5.240	0.033	13.131
1987	5.254	0.094	13.174
1988	5.262	0.122	13.310
1989	5.260	0.131	13.343
1990	5.285	0.169	13.384
1991	5.208	0.120	13.389
Units	Index	Index	Employees/Unit of Output

Note: Table 1B continued on next page.

Table 1B: Summary Statistics by Year; Final Goods; Productivity Measures and Channels (Cont.)

Determinants of Productivity Changes (Channels)									
Year	Tariffs	Intermediate Tariffs	Tot. Revenue (Log)	Foreign Input Dummy	Foreign Input Share	Foreign Raw Material Dummy	Foreign Raw Material Share	Share of Machinery and Investment	Herf Index
1977	48.6	32.2	16.286	N/A	N/A	0.255	0.087	0.12	0.036
1978	48.2	30.3	16.398	N/A	N/A	0.251	0.085	0.13	0.032
1979	48.3	30.2	16.402	N/A	N/A	0.236	0.081	0.13	0.030
1980	46.1	27.8	16.347	N/A	N/A	0.232	0.077	0.14	0.031
1981	45.6	26.6	16.327	0.151	0.056	0.225	0.075	0.15	0.031
1982	46.1	26.8	16.238	0.129	0.046	0.195	0.066	0.16	0.029
1983	61.7	35.8	16.494	0.145	0.048	0.204	0.070	0.15	0.030
1984	77.2	44.6	16.584	0.133	0.046	0.195	0.069	0.14	0.029
1985	51.6	33.3	16.560	0.128	0.049	0.194	0.069	0.11	0.033
1986	51.6	33.2	16.583	0.119	0.044	0.173	0.060	0.10	0.032
1987	54.0	32.8	16.632	0.110	0.041	0.165	0.059	0.10	0.035
1988	49.4	30.7	16.698	0.118	0.042	0.165	0.057	0.08	0.038
1989	48.8	29.6	16.694	0.113	0.039	0.160	0.054	0.09	0.044
1990	38.5	26.1	16.719	0.111	0.039	0.156	0.053	0.08	0.052
1991	28.4	19.2	16.724	0.119	0.041	0.161	0.053	0.09	0.065
Units	Percent	Percent	Real Pesos	Binary	Percent	Binary	Percent	Percent	Index

Table 1C: Summary Statistics by Year; Variables Used to Examine Impact of Tariff Changes on Channels

Year	Minimum Efficient Scale	Capital Intensity	Advert. Intensity	Market Size	Import Penetration	Export Intensity
1977	1,330,000,000	197,537	0.003	36,700,000,000	0.000	0.000
1978	1,770,000,000	211,609	0.004	42,400,000,000	0.154	0.060
1979	1,320,000,000	200,785	0.004	43,900,000,000	0.192	0.086
1980	1,440,000,000	196,648	0.006	41,300,000,000	0.303	0.109
1981	1,410,000,000	214,642	0.007	40,000,000,000	0.413	0.132
1982	1,230,000,000	242,038	0.009	41,000,000,000	0.498	0.151
1983	1,250,000,000	285,764	0.011	41,300,000,000	0.539	0.112
1984	1,440,000,000	281,908	0.013	44,600,000,000	0.626	0.119
1985	1,450,000,000	261,052	0.017	50,200,000,000	0.756	0.208
1986	1,630,000,000	253,285	0.023	56,100,000,000	1.058	0.334
1987	1,720,000,000	236,589	0.030	56,300,000,000	1.319	0.435
1988	1,860,000,000	244,089	0.038	58,700,000,000	1.517	0.632
1989	1,990,000,000	251,534	0.049	63,200,000,000	1.926	0.980
1990	2,000,000,000	255,603	0.063	69,700,000,000	2.510	1.520
1991	1,900,000,000	650,988	0.083	65,300,000,000	2.915	2.740
Units	Units of Output (Real Pesos)	Units of K / Employee (Real Pesos)	Percent	Units of Output (Real Pesos)	Percent	Percent

Note: Table 1C continued on next page.

Table 1C: Summary Statistics by Year; Variables Used to Examine Impact of Tariff Changes on Channels (Cont.)

Year	MESMSD	CDR1	EASTV	Total Employment	Skilled Employee Ratio	Avg. Wage
1977	38.9	310,804	2.4	73.0	0.188	71,985
1978	38.8	381,740	4.6	75.5	0.193	88,414
1979	38.0	400,527	3.9	76.0	0.189	83,382
1980	40.3	375,041	4.0	74.9	0.192	83,060
1981	42.7	397,501	5.0	72.8	0.193	84,030
1982	45.7	348,582	5.8	68.9	0.197	85,009
1983	45.8	456,673	5.2	74.4	0.208	90,131
1984	48.4	404,127	5.1	73.6	0.213	94,129
1985	49.7	531,827	3.6	70.0	0.228	91,783
1986	50.0	581,340	3.8	68.6	0.234	90,075
1987	50.8	592,245	4.3	70.7	0.237	89,311
1988	53.0	664,766	3.5	66.6	0.254	89,242
1989	49.6	730,637	8.7	65.0	0.250	88,610
1990	50.0	805,966	9.1	65.6	0.255	89,650
1991	46.8	779,929	8.7	67.2	0.266	179,967
Units	Unitless	Output/ Employee (Real Pesos)	Unitless	Employees	Percent	Pesos/ Year

Table 1D: Summary Statistics by Year; Factors of Production

Year	Herfindahl Index	Tariffs	Intermediate Tariffs	Capital	Labor	Energy	Raw Materials
1977	0.045	43.5	30.6	15,300,000	73.0	807,231	47,400,000
1978	0.042	42.3	28.5	17,400,000	75.5	997,554	50,400,000
1979	0.040	42.3	28.5	16,400,000	76.0	1,030,228	50,500,000
1980	0.041	39.4	25.9	16,000,000	74.9	1,075,338	51,400,000
1981	0.044	38.8	24.7	17,500,000	72.8	1,238,065	53,900,000
1982	0.044	39.2	24.9	21,100,000	68.9	1,355,197	51,700,000
1983	0.046	52.0	33.2	24,900,000	74.4	1,706,011	59,900,000
1984	0.047	64.8	41.3	24,400,000	73.6	1,958,326	67,300,000
1985	0.051	45.0	31.8	22,200,000	70.0	2,003,678	72,800,000
1986	0.050	44.9	31.6	20,900,000	68.6	2,209,450	75,500,000
1987	0.051	45.6	31.1	19,900,000	70.7	2,286,245	79,700,000
1988	0.057	42.0	29.1	19,400,000	66.6	2,302,156	87,300,000
1989	0.063	41.2	28.0	19,500,000	65.0	2,305,686	88,600,000
1990	0.069	34.1	24.9	19,800,000	65.6	2,449,999	92,800,000
1991	0.077	24.7	18.3	54,500,000	67.2	2,644,468	95,200,000
Units				Real Pesos	Employees	Real Pesos	Real Pesos

Table 2A: Summary Statistics by SIC Code; All Products; Productivity Measures and Channels

	Productivity Measures		
SIC Code	L&P TFP (Log)	Index TFP (Log)	Labor Prod. (Log)
311	3.102	-0.050	13.989
312	3.192	-0.073	14.276
313	7.108	-0.023	14.120
314	7.385	-0.203	13.299
321	6.530	-0.061	13.284
322	6.654	0.143	13.002
323	5.187	-0.109	13.107
324	2.518	-0.039	12.846
331	6.948	0.057	13.152
332	6.658	-0.055	12.559
341	2.666	-0.080	13.809
342	6.770	-0.130	12.789
351	3.929	-0.154	14.481
352	3.929	-0.091	13.702
355	7.451	-0.109	13.358
356	4.450	-0.084	13.342
361	8.067	-0.093	12.350
362	1.601	0.009	13.205
369	4.585	-0.068	13.000
371	5.368	-0.194	13.699
372	4.090	-0.291	13.548
381	4.754	-0.062	13.066
382	11.240	0.016	13.120
383	-1.796	-0.074	13.415
384	5.052	-0.104	12.992
385	5.790	0.040	13.026
Units	Index	Employees/Unit of Output	Index

Note: Table 2A continued on next page.

Table 2A: Summary Statistics by SIC Code; All Products; Productivity Measures and Channels (Cont.)

Determinants of Productivity Changes (Channels)									
SIC Code	Tariffs	Intermediate Tariffs	Tot. Revenue (Log)	Foreign Input Dummy	Foreign Input Share	Foreign Raw Material Dummy	Foreign Raw Material Share	Share of Machinery and Investment	Herf Index
311	36.2	32.8	17.326	0.096	0.036	0.162	0.068	0.081	0.010
312	31.5	32.6	17.584	0.213	0.040	0.287	0.058	0.119	0.027
313	54.4	34.1	18.824	0.274	0.057	0.442	0.078	0.092	0.035
314	31.1	33.5	17.210	0.263	0.034	0.293	0.026	0.048	0.226
321	53.8	N/A	17.003	0.190	0.058	0.200	0.061	0.192	0.041
322	71.5	34.6	16.352	0.029	0.009	0.039	0.011	0.079	0.020
323	39.0	34.5	16.624	0.223	0.030	0.296	0.040	0.117	0.072
324	62.5	N/A	16.029	0.065	0.010	0.085	0.012	0.108	0.051
331	41.9	34.0	16.169	0.071	0.021	0.094	0.021	0.123	0.114
332	50.8	33.6	15.735	0.034	0.007	0.055	0.011	0.101	0.024
341	31.4	24.9	17.533	0.213	0.069	0.264	0.074	0.161	0.076
342	37.2	24.8	16.039	0.138	0.058	0.241	0.094	0.286	0.058
351	20.7	24.7	18.357	0.500	0.225	0.556	0.232	0.222	0.106
352	19.9	24.8	17.425	0.535	0.215	0.664	0.274	0.059	0.039
355	42.1	24.9	16.851	0.425	0.193	0.511	0.248	0.151	0.126
356	54.0	N/A	16.859	0.293	0.104	0.367	0.158	0.258	0.032
361	46.7	25.2	16.087	0.340	0.086	0.474	0.146	0.185	0.126
362	32.6	25.0	17.010	0.381	0.150	0.488	0.189	0.123	0.111
369	29.3	25.1	16.487	0.104	0.043	0.159	0.050	0.210	0.030
371	19.2	19.8	17.475	0.335	0.177	0.438	0.213	0.215	0.102
372	18.7	19.8	16.989	0.418	0.262	0.440	0.261	0.119	0.125
381	37.7	19.8	16.384	0.204	0.084	0.326	0.134	0.126	0.044
382	21.0	25.7	16.451	0.281	0.098	0.434	0.161	0.154	0.157
383	31.3	25.3	17.152	0.526	0.257	0.626	0.293	0.650	0.068
384	29.5	25.6	16.619	0.306	0.138	0.421	0.182	0.187	0.121
385	23.1	25.2	16.455	0.360	0.180	0.463	0.235	0.111	0.165
Units	Percent	Percent	Pesos	Binary	Percent	Binary	Percent	Percent	Index

Table 2B: Summary Statistics by SIC Code; Final Goods; Productivity Measures and Channels

	Productivity Measures		
SIC Code	L&P TFP (Log)	Index TFP (Log)	Labor Prod.
311	2.974	-0.097	13.518
312	3.199	0.016	14.010
313	7.108	-0.023	14.120
321	6.546	-0.063	13.387
322	6.654	0.143	13.002
324	2.518	-0.039	12.846
332	6.658	-0.055	12.559
342	6.770	-0.130	12.789
352	3.956	-0.079	13.643
361	8.067	-0.093	12.350
381	4.679	-0.064	12.888
383	-1.649	-0.061	13.390
384	5.027	-0.116	12.986
385	5.780	-0.021	12.864
Units	Index	Employees/Unit of Output	Index

Note: Table 2B continued on next page.

Table 2B: Summary Statistics by SIC Code; Final Goods; Productivity Measures and Channels (Cont.)

	Determinants of Productivity Changes (Channels)								
SIC Code	Tariffs	Intermediate Tariffs	Tot. Revenue (Log)	Foreign Input Dummy	Foreign Input Share	Foreign Raw Material Dummy	Foreign Raw Material Share	Share of Machinery and Investment	Herf Index
311	36.3	32.8	16.798	0.055	0.008	0.115	0.021	0.081	0.010
312	32.4	32.8	17.976	0.300	0.089	0.339	0.093	0.054	0.027
313	54.4	34.1	18.824	0.274	0.057	0.442	0.078	0.092	0.035
321	54.3	N/A	16.557	0.325	0.085	0.315	0.088	0.077	0.041
322	71.5	34.6	16.352	0.029	0.009	0.039	0.011	0.079	0.020
324	62.5	N/A	16.029	0.065	0.010	0.085	0.012	0.108	0.051
332	50.8	33.6	15.735	0.034	0.007	0.055	0.011	0.101	0.024
342	37.2	24.8	16.039	0.138	0.058	0.241	0.094	0.286	0.058
352	19.9	24.7	17.521	0.543	0.232	0.692	0.296	0.059	0.038
361	46.7	25.2	16.087	0.340	0.086	0.474	0.146	0.185	0.126
381	37.9	19.8	16.221	0.191	0.081	0.390	0.158	0.111	0.043
383	32.0	25.5	17.085	0.471	0.200	0.675	0.272	0.305	0.062
384	29.5	25.6	16.548	0.297	0.127	0.421	0.173	0.186	0.121
385	23.2	25.2	16.106	0.601	0.426	0.682	0.515	0.163	0.160
Units	Percent	Percent	Pesos	Binary	Percent	Binary	Percent	Percent	Index

Table 2C: Summary Statistics by SIC Code; Variables Used to Examine Impact of Tariff Changes on Channels

SIC Code	Minimum Efficient Scale	Capital Intensity	Advert. Intensity	Market Size	Import Penetration	Export Intensity
311	2,190,000,000	283,977	0.014	180,000,000,000	0.129	0.190
312	1,610,000,000	339,573	0.030	42,800,000,000	0.079	0.223
313	3,060,000,000	332,368	0.150	62,200,000,000	0.069	0.012
314	3,520,000,000	277,103	0.053	7,630,000,000	0.146	0.463
321	2,520,000,000	271,484	0.015	59,900,000,000	0.165	0.647
322	256,000,000	52,366	0.015	29,200,000,000	0.104	1.428
323	978,000,000	100,220	0.024	7,530,000,000	0.102	1.849
324	634,000,000	76,250	0.017	7,710,000,000	0.040	0.966
331	742,000,000	226,291	0.012	5,870,000,000	0.179	0.322
332	77,800,000	70,268	0.029	3,000,000,000	0.069	0.319
341	2,750,000,000	498,844	0.009	31,600,000,000	0.775	0.118
342	1,210,000,000	242,886	0.023	16,200,000,000	0.402	1.119
351	4,060,000,000	704,384	0.017	56,700,000,000	2.890	0.521
352	1,440,000,000	197,424	0.076	49,800,000,000	0.582	0.123
355	3,570,000,000	185,828	0.022	13,000,000,000	0.467	0.161
356	551,000,000	295,583	0.025	20,000,000,000	0.171	0.167
361	747,000,000	195,388	0.018	3,570,000,000	0.145	0.519
362	2,660,000,000	261,395	0.031	8,520,000,000	0.325	0.294
369	1,200,000,000	669,956	0.017	24,600,000,000	0.125	0.278
371	6,010,000,000	1,201,123	0.012	29,700,000,000	1.797	0.699
372	1,550,000,000	257,843	0.017	4,740,000,000	4.211	0.207
381	481,000,000	154,398	0.023	26,800,000,000	0.955	0.327
382	596,000,000	119,322	0.028	14,200,000,000	9.629	0.385
383	1,080,000,000	1,040,127	0.037	23,700,000,000	2.944	0.209
384	8,260,000,000	266,922	0.027	34,500,000,000	2.933	0.142
385	1,020,000,000	211,898	0.035	3,820,000,000	4.654	0.432
Units	Units of Output (Real Pesos)	Units of K / Employee (Real Pesos)	Percent	Units of Output (Real Pesos)	Percent	Percent

Note: Table 2C continued on next page.

Table 2C: Summary Statistics by SIC Code; Variables Used to Examine Impact of Tariff Changes on Channels (Cont.)

SIC Code	MESMSD	CDR1	EASTV	Total Employment	Skilled Employee Ratio	Avg. Wage
311	83.0	1	0.0	64.3	0.257	83,111
312	26.4	2,276,126	0.0	52.0	0.293	99,718
313	20.6	2,333,484	2.5	196.7	0.401	142,363
314	2.2	1,211,447	2.2	167.1	0.187	90,129
321	24.5	755,231	6.3	116.7	0.191	83,068
322	116.7	1	0.0	51.4	0.153	64,207
323	7.7	744,331	5.6	73.1	0.162	75,178
324	13.4	558,728	8.1	48.2	0.123	66,507
331	8.3	720,706	8.3	33.9	0.171	71,906
332	39.1	18,001	0.0	37.6	0.167	69,251
341	11.7	1,738,497	11.7	79.4	0.237	117,318
342	14.1	453,797	8.9	57.4	0.260	85,336
351	14.1	3,624,248	14.1	122.5	0.332	166,615
352	35.1	143,597	5.1	85.2	0.382	119,728
355	3.7	865,926	3.7	91.3	0.236	97,541
356	36.6	33,145	0.0	61.3	0.215	89,106
361	4.8	348,741	4.8	156.6	0.131	75,610
362	4.0	744,788	4.0	117.4	0.199	96,509
369	20.4	750,452	0.0	66.7	0.173	90,127
371	5.1	1,991,038	5.1	199.3	0.188	102,261
372	3.0	1,246,397	3.0	67.5	0.251	100,871
381	56.2	1	11.3	51.0	0.199	83,801
382	24.5	548,343	22.8	48.7	0.217	91,168
383	22.1	1,030,617	14.7	87.2	0.265	311,582
384	4.7	673,008	4.7	92.9	0.204	93,762
385	5.1	747,151	5.1	49.9	0.260	89,948
Units	Unitless	Output/ Employee (Real Pesos)	Unitless	Employees	Percent	Real Pesos/ Year

Table 2D: Summary Statistics by SIC Code; Factors of Production

SIC Code	Capital	Labor	Energy	Raw Materials
311	18,300,000	64.3	1,434,474	128,000,000
312	17,700,000	52.0	1,712,987	147,000,000
313	64,500,000	196.7	4,895,370	173,000,000
314	47,900,000	167.1	1,963,889	205,000,000
321	31,000,000	116.7	2,605,133	67,000,000
322	2,722,578	51.4	167,668	14,900,000
323	7,303,361	73.1	893,479	57,900,000
324	3,698,352	48.2	286,275	19,300,000
331	7,731,350	33.9	618,044	12,300,000
332	2,631,235	37.6	191,476	8,263,198
341	39,600,000	79.4	6,882,753	140,000,000
342	14,000,000	57.4	447,873	27,900,000
351	86,000,000	122.5	10,800,000	262,000,000
352	16,800,000	85.2	884,618	102,000,000
355	16,600,000	91.3	2,985,681	93,100,000
356	18,000,000	61.3	1,909,658	52,800,000
361	32,300,000	156.6	4,215,435	34,800,000
362	30,300,000	117.4	4,762,607	43,900,000
369	46,200,000	66.7	4,546,760	29,400,000
371	228,000,000	199.3	20,100,000	190,000,000
372	17,400,000	67.5	3,048,701	85,700,000
381	7,879,711	51.0	719,333	27,100,000
382	5,827,158	48.7	550,980	26,100,000
383	91,700,000	87.2	1,061,479	69,400,000
384	24,700,000	92.9	1,024,452	149,000,000
385	10,800,000	49.9	573,178	25,300,000
Units	Real Pesos	Employees	Real Pesos	Real Pesos

Table 3

Effect of Trade Liberalization on Extensive Margin of Foreign Input Use

	Foreign Input Use (Binary)	Foreign Input Use (Binary)
Input Tariffs	-0.725	N/A
	31.07**	N/A
Output Tariffs	N/A	-0.557
	N/A	40.15**
Scale (Total Employment)	0.003	0.003
	54.56**	64.71**
Share of Skilled Employees in Total Employment	0.498	0.342
	30.69**	21.34**
Average Wage	0.000003	0.000003
	70.45**	67.38**
Constant	0.046	0.333
	-0.89	4.30**
Observations	60,626	71,681
Method	Probit	Probit

Notes: Z statistics are presented below coefficient estimates. * and ** denote statistical significance at the 5 and 1 percent level, respectively.

Table 4
Effect of Trade Liberalization on New Investment

	New Investment in Machinery and Equipment	New Investment in Machinery and Equipment
Input Tariffs	-0.008	N/A
	2.06*	N/A
Output Tariffs	N/A	-0.002
	N/A	-1.4
Scale (Total Employment)	0.067	0.028
	-0.16	-0.08
Share of Skilled Employees in Total Employment	0.002	0.004
	-0.02	-0.04
Average Wage	-0.042	-0.036
	-0.04	-0.04
Constant	0.383	0.255
	3.05**	3.04**
Observations	82,337	96,925
Method	Fixed Effects	Fixed Effects

Notes: Z statistics are presented below coefficient estimates. * and ** denote statistical significance at the 5 and 1 percent level, respectively.

Table 5
Effect of Trade Liberalization on Herfindahl Index

	Herfindahl Index	Herfindahl Index	Herfindahl Index
Lagged Herfindahl Index	N/A	N/A	0.54
	N/A	N/A	10.55**
Output Tariffs	0.002	N/A	0.002
	-0.66	N/A	-1.00
Lagged Output Tariffs	N/A	-0.0004	N/A
	N/A	-0.16	N/A
Minimum Efficient Scale	0.63	0.55	-0.17
	3.69**	3.34**	-1.40
Capital Intensity	0.001	0.001	0.001
	-0.37	-0.43	-0.52
Advertising Intensity	-0.05	-0.06	0.15
	-1.28	-1.60	3.51**
Domestic Market Size	-0.02	-0.02	0.03
	-1.19	-1.33	-1.67
Export Intensity	-0.01	-0.01	0.004
	2.54*	3.04**	1.99*
Constant	0.07	0.08	0.004
	5.67**	5.56**	5.35**
Observations	390	364	338
Method	Fixed Effects	Fixed Effects	GMM

Notes: Z statistics are presented below coefficient estimates. * and ** denote statistical significance at the 5 and 1 percent level, respectively.

Table 6

Effect of Trade Liberalization on Plant Scale

	Total Output	Total Output
Input Tariffs	-0.023	N/A
	-0.87	N/A
Output Tariffs	N/A	-0.019
	N/A	-1.54
Import Penetration	0.052	0.042
	3.11**	2.46*
MESMSD	0.002	0.001
	10.08**	10.35**
CDR	0.00005	0.00005
	18.00**	18.12**
EASTV	-0.001	-0.001
	5.99**	4.84**
Constant	16.661	16.666
	183.90**	360.40**
Observations	82,337	96,925
Method	Fixed Effects	Fixed Effects

Notes: Z statistics are presented below coefficient estimates. * and ** denote statistical significance at the 5 and 1 percent level, respectively. Import penetration is the initial level of import penetration in 1978--the first year when trade data are available.

Table 7
Effect of Trade Liberalization on Foreign Input Share

	Foreign Input Share	Foreign Input Share
Input Tariffs	-0.001	N/A
	-0.24	N/A
Output Tariffs	N/A	-0.003
	N/A	-1.25
Scale (Total Employment)	0.012	0.02
	-1.52	2.66**
Share of Skilled Employees in Total Employment	-0.435	-0.35
	-0.27	-0.22
Average Wage	0.03	0.03
	-1.78	-1.79
Constant	0.07	0.074
	3.98**	8.43**
Observations	60,626	71,681
Method	Fixed Effects	Fixed Effects

Notes: Z statistics are presented below coefficient estimates. * and ** denote statistical significance at the 5 and 1 percent level, respectively.

Table 8A: Potential Determinants of Productivity Growth (Labor Productivity)

	1 Lab Prod	2 Lab Prod	3 Lab Prod	4 Lab Prod	5 Lab Prod	6 Lab Prod
Lagged Productivity	.. ..	0.246 17.53**	.. ..	0.217 11.55**	.. ..	0.229 11.25**
Scale	.. ..	.. ..	.. ..	.. ..	.. ..	.. ..
Foreign Input Dummy	0.1 11.33**	0.042 4.35**	0.074 7.11**	0.044 3.98**	0.065 5.66**	0.047 3.84**
Foreign Input Share	.. ..	.. ..	.. ..	.. ..	.. ..	.. ..
Investment in Machinery	-0.619 2.23*	-0.179 -0.64	-0.083 -0.33	0.077 0.3	-0.074 -0.3	0.115 0.45
Investment in Machinery Four Year Lag	.. ..	.. ..	32.178 2.11*	19.609 1.36	30.078 1.83	13.499 0.89
Herfindahl Index	.. ..	.. ..	.. ..	.. ..	.. ..	.. ..
Output Tariff	.. ..	.. ..	.. ..	.. ..	-0.167 5.81**	-0.104 2.99**
Input Tariff	.. ..	.. ..	.. ..	.. ..	0.362 6.23**	0.375 4.97**
Observations	71,681	51,612	37,316	30,359	32,015	25,984
Technique	FE	GMM	FE	GMM	FE	GMM

Notes: All regressions include year, industry and plant fixed effects. * and ** denote statistical significance at the 5 and 1 percent level, respectively. Table 8A is continued on next page.

Table 8A: Potential Determinants of Productivity Growth (Labor Productivity) (Cont.)

	7 Lab Prod	8 Lab Prod	9 Lab Prod	10 Lab Prod	11 Lab Prod	12 Lab Prod
Lagged Productivity	.. ..	0.247 17.60**	.. ..	0.247 17.57**	.. ..	0.184 17.45**
Scale	.. ..	.. ..	.. ..	.. ..	0.657 191.92**	0.778 170.43**
Foreign Input Dummy	0.099 11.22**	0.042 4.37**	0.077 7.21**	0.026 2.32*	-0.031 3.70**	-0.015 -1.76
Foreign Input Share	.. ..	.. ..	0.083 3.61**	0.062 2.52*	0.033 1.83	0.019 1.03
Investment in Machinery	-0.615 2.22*	-0.19 -0.68	-0.622 2.25*	-0.195 -0.7	-0.21 0.98	-0.02 0.07
Investment in Machinery Four Year Lag	.. ..	.. ..	.. ..	.. ..	.. ..	.. ..
Herfindahl Index	-1.04 9.57**	-0.952 6.24**	-1.041 9.57**	-0.95 6.23**	-0.33 3.88**	-0.246 2.12*
Output Tariff	.. ..	.. ..	.. ..	.. ..	.. ..	.. ..
Input Tariff	.. ..	.. ..	.. ..	.. ..	.. ..	.. ..
Observations	71,681	51,612	71,681	51,612	71,681	51,612
Technique	FE	GMM	FE	GMM	FE	GMM

Notes: All regressions include year, industry and plant fixed effects. * and ** denote statistical significance at the 5 and 1 percent level, respectively.

Table 8B: Potential Determinants of Productivity Growth (Levinsohn & Petrin TFP)

	1 L&P TFP	2 L&P TFP	3 L&P TFP	4 L&P TFP	5 L&P TFP	6 L&P TFP
Lagged Productivity	.. ..	-0.014 2.91**	.. ..	0.015 3.88**	.. ..	0.015 3.62**
Scale	.. ..	.. ..	.. ..	.. ..	.. ..	.. ..
Foreign Input Dummy	0.024 3.83**	0.008 1.21	0.01 1.43	0.014 1.87	0.005 0.59	0.012 1.47
Foreign Input Share	.. ..	.. ..	.. ..	.. ..	.. ..	.. ..
Investment in Machinery	-1.123 5.69**	-0.65 3.54**	-0.841 5.10**	-0.568 3.41**	-0.838 4.96**	-0.558 3.27**
Investment in Machinery Four Year Lag	.. ..	.. ..	-7.379 -0.72	-1.51 -0.16	.. ..	-4.118 -0.4
Herfindahl Index	.. ..	.. ..	.. ..	.. ..	.. ..	.. ..
Output Tariff	.. ..	.. ..	.. ..	.. ..	-0.074 3.76**	-0.098 4.31**
Input Tariff	.. ..	.. ..	.. ..	.. ..	0.133 3.35**	0.143 2.72**
Observations	71,681	51,612	37,316	30,359	32,015	25,984
Technique	FE	GMM	FE	GMM	FE	GMM

Notes: All regressions include year, industry and plant fixed effects. * and ** denote statistical significance at the 5 and 1 percent level, respectively. Table 8B is continued on next page.

Table 8B: Potential Determinants of Productivity Growth (Levinsohn & Petrin TFP) (Cont.)

	7 L&P TFP	8 L&P TFP	9 L&P TFP	10 L&P TFP	11 L&P TFP	12 L&P TFP
Lagged Productivity	.. ..	-0.013 2.81**	.. ..	-0.013 2.80**	.. ..	-0.011 2.50*
Scale	.. ..	.. ..	.. ..	.. ..	0.259 88.95**	0.325 91.89**
Foreign Input Dummy	0.023 3.61**	0.008 1.22	0.022 2.92**	0.012 1.56	-0.02 2.87**	-0.006 -0.88
Foreign Input Share	.. ..	.. ..	0.002 0.1	-0.016 -0.99	-0.018 -1.18	-0.034 2.31*
Investment in Machinery	-1.117 5.68**	-0.66 3.60**	-1.118 5.68**	-0.659 3.59**	-0.001 5.17**	-0.001 3.43**
Investment in Machinery Four Year Lag	.. ..	.. ..	.. ..	.. ..	.. ..	.. ..
Herfindahl Index	-1.338 17.32**	-0.715 7.19**	-1.338 17.32**	-0.715 7.20**	-1.057 14.58**	-0.439 4.78**
Output Tariff	.. ..	.. ..	.. ..	.. ..	.. ..	.. ..
Input Tariff	.. ..	.. ..	.. ..	.. ..	.. ..	.. ..
Observations	71,681	51,612	71,681	51,612	71,681	51,612
Technique	FE	GMM	FE	GMM	FE	GMM

Notes: All regressions include year, industry and plant fixed effects. * and ** denote statistical significance at the 5 and 1 percent level, respectively.

Table 8C: Potential Determinants of Productivity Growth (TFP Index)

	1 TFP	2 TFP	3 TFP	4 TFP	5 TFP	6 TFP
Lagged Productivity	.. ..	0.262 22.27**	.. ..	0.372 14.53**	.. ..	0.377 14.32**
Scale	.. ..	.. ..	.. ..	.. ..	.. ..	.. ..
Foreign Input Dummy	-0.001 -0.22	0.001 0.18	-0.009 1.11	0.003 0.34	-0.009 1.1	0.003 0.32
Foreign Input Share	.. ..	.. ..	.. ..	.. ..	.. ..	.. ..
Investment in Machinery	-2.824 95.99**	-3.44 82.20**	-2.937 65.05**	-3.46 63.14**	-3.022 59.34**	-3.556 59.34**
Investment in Machinery Four Year Lag	.. ..	.. ..	-0.043 2.68**	-0.046 1.97*	-0.066 3.66**	-0.094 2.97**
Herfindahl Index	.. ..	.. ..	.. ..	.. ..	.. ..	.. ..
Output Tariff	.. ..	.. ..	.. ..	.. ..	0.166 8.19**	0.015 -0.54
Input Tariff	.. ..	.. ..	.. ..	.. ..	-0.578 14.16**	-0.02 -0.3
Observations	46,350	27,377	25,320	17,024	22,652	15,353
Technique	FE	GMM	FE	GMM	FE	GMM

Notes: All regressions include year, industry and plant fixed effects. * and ** denote statistical significance at the 5 and 1 percent level, respectively. Table 8C is continued on next page.

Table 8C: Potential Determinants of Productivity Growth (TFP Index) (Cont.)

	7 TFP	8 TFP	9 TFP	10 TFP	11 TFP	12 TFP
Lagged Productivity	.. ..	0.258 22.02**	.. ..	0.258 22.02**	.. ..	0.242 21.55**
Scale	.. ..	.. ..	.. ..	.. ..	0.1 27.90**	0.214 41.83**
Foreign Input Dummy	-0.002 -0.31	0.002 0.2	-0.015 -1.94	0.002 -0.18	-0.025 3.31**	-0.004 -0.45
Foreign Input Share	.. ..	.. ..	0.051 3.09**	0.00 0.02	0.044 2.70**	-0.008 -0.45
Investment in Machinery	-2.827 96.13**	-3.439 82.31**	-2.827 96.15**	-3.439 82.31**	-2.685 90.91**	-2.973 71.54**
Investment in Machinery Four Year Lag	.. ..	.. ..	.. ..	.. ..	.. ..	.. ..
Herfindahl Index	-0.532 6.39**	-0.482 3.88**	-0.532 6.39**	-0.483 3.89**	-0.533 6.48**	-0.39 3.26**
Output Tariff	.. ..	.. ..	.. ..	.. ..	.. ..	.. ..
Input Tariff	.. ..	.. ..	.. ..	.. ..	.. ..	.. ..
Observations	46,350	27,377	46,350	27,377	46,350	27,377
Technique	FE	GMM	FE	GMM	FE	GMM

Notes: All regressions include year, industry and plant fixed effects. * and ** denote statistical significance at the 5 and 1 percent level, respectively.

Chapter 3: Concording U.S. Harmonized System Categories Over Time[1]

Section 1: Introduction

This paper serves three purposes. First, it outlines an algorithm for concording ten-digit U.S. Harmonized System (HS) product codes over time. Second, it describes how this algorithm can be used to construct an export- or import-code concordance for any arbitrary beginning and ending years from 1989 to 2007. Finally, it summarizes the 1989 to 2004 HS concordances used in Bernard, Jensen, Redding and Schott's (2009) analysis of the margins of U.S. trade and provides statistics illustrating the prevalence of changes in HS codes during that time interval. We note that though the official names of U.S. export and import product codes are "Schedule B" and "Harmonized Tariff Schedule" codes, respectively, we refer to both generically as HS codes in this paper.

Section 2 provides a brief description of HS codes. Section 3 describes the data used to construct our concordance. Section 4 outlines our algorithm. Section 5 summarizes the 1989 to 2004 concordance. An appendix contains the Stata computer code and describes the input files used to generate concordances.

Section 2: Brief Description of HS Codes

U.S. HS codes are based on the Harmonized System established by the World Customs Organization (WCO). The WCO assigns 6-digit codes for general

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categories, and countries adopting the system then define their own codes to capture commodities at more detailed levels. In the United States, the most detailed level of disaggregation is ten digits. In this paper, we refer to ten-digit codes as “product” or “goods” categories. U.S. export codes are administered by the United States Census Bureau (Census). U.S. import codes are administered by the U.S. International Trade Commission (USITC).

Changes to U.S. export or import product codes can occur via three routes: changes by the WCO to the official list of international six-digit prefixes; U.S. legislation that affects U.S. eight-digit codes (imports only); and changes by the Committee for Statistical Annotation of Tariff Schedules (known as the “484(f) Committee”) to statistical ten-digit codes.[2]

HS codes are updated for several reasons. The WCO, for example, makes adjustments to eliminate six-digit roots that capture little or no trade, with a goal of having trade roughly balanced across codes. In addition, the 484(f) Committee may split a single HS code into several new codes in order to report import or export data at a more detailed level. Similarly, producers may petition one of the official bodies noted above for code changes to obtain a higher profile for the goods they export or import.

Section 3: Data

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[2] See http://www.census.gov/foreign-trade/aip/comb_seminar_pres.ppt, and www.census.gov/foreign-trade/faq/sb/sb0008.html for more detail.

Each year, Census publishes documents outlining the HS codes that have become "obsolete" and the "new" codes that will take their place. We refer to these documents as Census' "new-obsolete" files. For exports, HS-code changes take effect annually in January; for imports, they can occur within as well as across years. New-obsolete files for years before 1997 are available only in hard copy and were transcribed into electronic form as part of the construction of our concordance. These files as well as electronic versions of subsequent files were obtained from Mayumi Hairston Escalante at Census. The most recent new-obsolete files are currently posted on the Census website.[3]

We use the terms "simple" and "complex" to describe the two basic changes to HS codes that can occur in a new-obsolete file.[4] Simple changes make no adjustments to the actual items covered by a particular code, they just swap one ten-digit code for another. There are several possible reasons for a one-to-one re-numbering, including:

1. To align the Schedule B and HTS codes where Census finds their descriptions are the same;
2. To differentiate the Schedule B and HTS codes where Census has found them to be different;

---

[3] See http://www.census.gov/foreign-trade/schedules/b/#obsolete and http://www.usitc.gov/tata/hts/index.htm, respectively.

[4] Some new-obsolete files contain "blanket" mappings, our term for mappings that include codes ending in a series of X's, e.g., 8486XXXXXX. We drop these observations.

3. To correct errors by reclassifying a commodity under a different subheading;
4. To maintain the level of statistical detail after a revision of the 6- or 8-digit codes; and
5. To accommodate a new numbering pattern, usually the result of another code being broken out.

In contrast to simple changes, complex changes alter the mix of items captured by a particular code. For these changes, the items formerly encompassed by one or more "obsolete" codes are distributed to one or more "new" codes. In 2002, for example, various types of waste oil, which previously were grouped with the fresh oils to which they were most similar, were given their own HS codes. As a result, the (now obsolete) former fresh oil product categories were linked to the new waste oil categories from which they emerged.

For each set of new-obsolete mappings in a particular new-obsolete file, we construct a synthetic HS code, which we refer to as a "setyear" (setyr in our Stata code). This synthetic code records both the count of the change since the first change in 1989 and an identifier for when it takes place. Formally, for exports, it is defined as the count of the particular mapping plus the four-digit year in which the change occurs divided by 10,000. For imports, it is the count of the particular mapping plus six-digit year-month in which the change occurs divided by 1,000,000. The very first setyears for exports and imports, for example, are equal to 1.1989 and 1.198906.

Table 1 summarizes the number of new-obsolete mappings in the raw data for export and import codes, respectively. Results for export codes are displayed in the left panel while those for import codes are displayed in the middle and right panels. The first column of each panel notes the year-month in which the noted changes take place. The second and third columns report the total number of retired and replacement codes encompassed by the number of sets reported in column four. Note that the number of sets in column four is smaller than the numbers of HS codes in columns two and three because multiple codes are often involved in a particular change. The fifth column reports the number of changes that are "simple" in the sense outlined above.

As indicated in the table, HS codes are updated unevenly in the sense that some years (e.g., 2002) encompass substantially more changes than others (e.g. 2000).

Section 4: Developing an HS Concordance

Concording HS codes over time is complicated by the existence of chains of HS-code changes across months and years into "family trees." There are two basic types of family tree. We refer to the first case, displayed in Figure 1, generically as a "growing family tree." In this case, code *a* from period *t* may become obsolete and be mapped to new codes *b* and *c* in period *t+1*. Then, in period *t+2*, codes *b* and *c* may become obsolete and be mapped to new codes *e* and *f*, and *g* and *h*, respectively. Our concordance of the period *t* to period *t+2* HS codes assigns a common synthetic code to all HS codes in a growing family tree. Such an assignment may result in potentially many more HS codes being mapped to a given synthetic code in the final year of the concordance than in the first year.[5]

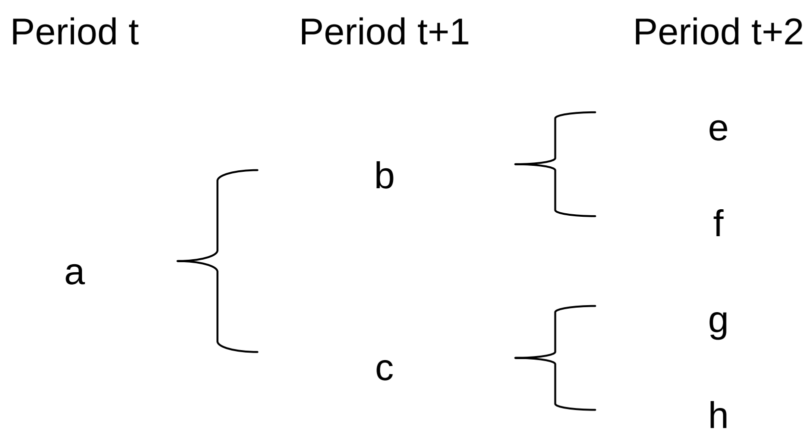

Figure 1: Growing Family Tree

The second type of family tree, which we refer to generically as a "shrinking family tree," is displayed in Figure 2. In this case, codes *a* and *b*, and *c* and *d*, from period *t* separately become obsolete and mapped to codes *e* and *f*, respectively, in period *t+1*. Then, in period *t+2*, codes *e* and *f* become obsolete and are assigned to new code *g*. In this case, the number of HS codes mapped to the family's common synthetic code declines over time.[6]

[5] In 1997, for example, 7802000000 is mapped to 7802000030 and 7802000060. In a 1996 to 1997 concordance, we would assign a single synthetic HS code to all of these actual HS codes.

[6] In 1997, for example, 8506800010 and 8506800050 are mapped to 8506800000. In a 1996 to 1997 concordance, we would assign a single synthetic HS code to all of these actual HS codes.

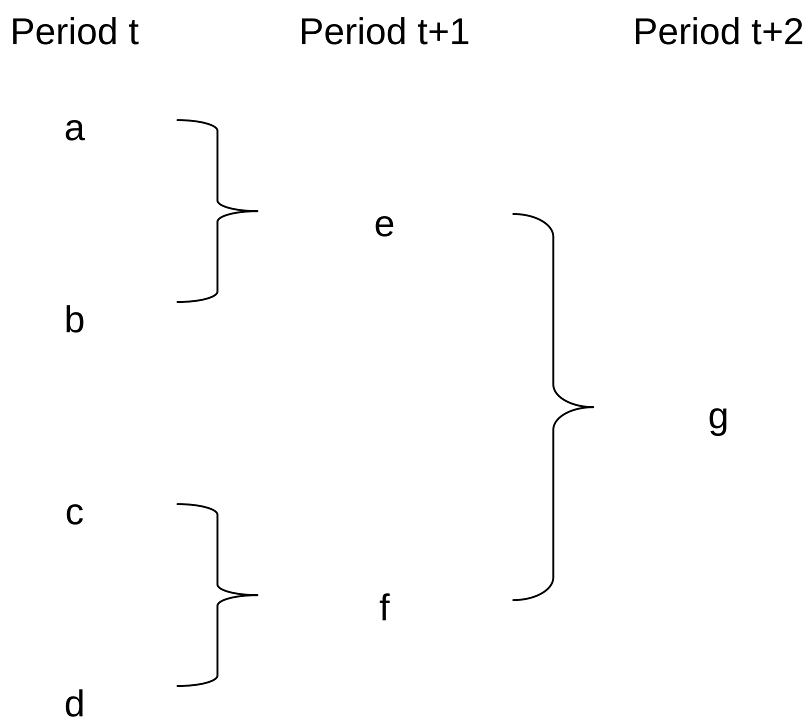

Figure 2: Shrinking Family Tree

The algorithm we develop for concording HS codes between arbitrary beginning and ending year-months accounts for both types of family trees, as well as combinations of the two types. Though specific details about how the algorithm is implemented can be determined by examining the Stata code in the Appendix, the basic steps are as follows:

1. Read in raw obsolete-new mappings;
2. Assign a single setyear to each obsolete-new mapping appearing in the raw files;
3. Choose a beginning and end year for the concordance;

4. Identify family trees extending between the beginning and end years of the concordance; and
5. Assign all members of a family tree the minimum setyear among family members within the time-frame of the concordance. Note that the part of the setyear after the decimal point identifies the year in which the family tree starts (i.e., period *t* in Figures 1 and 2 above). In the Stata code below, a separate variable (named effyr) identifies the year in which a particular new-obsolete mapping occurs.[7]

Step four is accomplished by successively merging subsequent obsolete-new mappings to all periods' new-obsolete mappings between the beginning and end years of the concordance. To bridge codes used from 1989 to 2004 for example, the chained file is constructed as follows. First, merge the new codes in the 1990 file to the obsolete codes in 1991 file, dropping any codes that are unique to 1991. Second, merge the obsolete codes in the 1992 file to the new codes in the previously merged 1990-1991 file, again dropping any codes unique to 1992. And so on. Note that this successive merging has to be done starting with every year-month between the beginning and ending year-month because chains can begin in any year-month, and

[7] For example, in 1998 export code 8531800035 from 1997 is mapped to code 8531804000. Then, in 2002, codes 8531804000 and 8527908015 from 2001 are mapped into 8527908600. The setyr for the family is 1404.1998. The integer part of this setyr indicates that the first mapping in the family, from 8531800035 to 8531804000, is the 1404th mapping since 1989. The part after the decimal point indicates it occurs in 1998. The effyr for the two mappings are 1998 and 2002, respectively.

they would be missed otherwise given the dropping just mentioned. After these chains are created, they are appended into a single file and added to all obsolete-new mappings that are not parts of a chain.

Section 5: A 1989-2004 Concordance

This section describes the 1989 to 2004 concordance used by Bernard, Jensen, Redding and Schott (2009) in their analysis of the margins of U.S. trade. The first and second columns of Table 2 summarize total U.S. exports in 1989 and 2004 and the total number of HS product categories exported in those two years, respectively. Columns three and four provide analogous detail with respect to U.S. imports. As indicated in the table, (nominal) exports more than double while (nominal) imports more than triple over the fifteen-year interval. The number of pre-concorded export and import HS codes observed in each year of data, by contrast, grow 13 percent and 21 percent, respectively.

Table 2: Trade in 1989 and 2004

	Exports		Imports	
	Value	Codes	Value	Codes
1989	354	7,853	468	13,941
2004	818	8,859	1,460	16,836

Notes: Export and import values in billions of U.S. dollars. Number of codes refers to number of original ten-digit HS categories in the raw trade data.

Table 3 reports two decompositions of export and import codes. The first three rows of the Table show how many of the original HS codes in each year survive versus being replaced by synthetic codes. The remaining rows in the table decompose the actual plus synthetic codes that remain after the concordance into those which are common across years and those which are idiosyncratic to a particular year.

Table 3: Distribution of Product Codes in Matched 1989 to 2004 U.S. Trade Data

	Exports				Imports			
	1989		2004		1989		2004	
Original HS Codes	7,853	100	8,859	100	13,941	100	16,836	100
Surviving Original Codes	5,349	68	5,341	60	8,585	62	8,508	51
Replaced by Synthetic Codes	2,504	32	3,518	40	5,356	38	8,328	49
Actual + Synthetic Codes After Concordance	6,978	89	6,971	79	12,262	88	12,240	73
Actual Codes	5,349	68	5,341	60	8,585	62	8,508	51
Common to both years	5,318	68	5,318	60	8,240	59	8,240	49
Appear in only one year	31	0	23	0	345	2	268	2
Synthetic Codes	1,629	21	1,630	18	3,677	26	3,732	22
Common to both years	1,624	21	1,624	18	3,570	26	3,570	21
Appear in only one year	5	0	6	0	107	1	162	1

Notes: Table decomposes the number of original HS codes in each year into those replaced by a synthetic code versus not, and total surviving HS plus synthetic codes in each year into noted sub-groups. All replacements are with respect to a 1989 to 2004 concordance. Even columns display values as a percent of first row in preceding column.

Of the 7,853 original HS codes appearing in the 1989 U.S. export data, for example, 2,504 are replaced by synthetic codes. Since the same synthetic code is often assigned to more than one original code, the resulting concorded dataset contains 6,978 actual plus synthetic codes. Of these, 5,349 and 1,629 are actual and synthetic, respectively. Each of these totals, in turn, can be broken down into actual codes which are common to both 1989 and 2004 (5,318), synthetic codes that are common to both 1989 and 2004 (1,624), actual codes unique to 1989 (31) and synthetic codes that are unique to 1989 (5). These breakdowns reveal that the number of actual and synthetic export and import goods actually added and dropped between 1989 and 2004 is relatively small.

The values of U.S. exports and imports associated with each of the cells in Table 3 are reported in Table 4. As indicated below, synthetic codes account for the majority of import value in both 1989 and 2004.

Table 4: Distribution of Value in Matched 1989 to 2004 Trade Data

	Exports				Imports			
	1989		2004		1989		2004	
Original HS Codes	353,766	100	817,936	100	468,012	100	1,460,160	100
Surviving Original Codes	206,556	58	428,571	52	178,545	38	550,049	38
Replaced by Synthetic Codes	147,210	42	389,365	48	289,467	62	910,111	62
Actual + Synthetic Codes After Concordance	353,766	100	817,936	100	468,012	100	1,460,160	100
Actual Codes	206,555	58	428,571	52	178,545	38	550,049	38
Common to both years	188,832	53	408,903	50	175,517	38	537,508	37
Appear in only one year	17,723	5	19,668	2	3,028	1	12,541	1
Synthetic Codes	147,210	42	389,366	48	289,466	62	910,111	62
Common to both years	147,143	42	388,971	48	288,273	62	906,775	62
Appear in only one year	67	0	395	0	1,193	0	3,336	0

Notes: Table decomposes U.S export and import value according to whether HS codes are original or synthetic. All replacements are with respect to a 1989 to 2004 concordance. Values are in millions of U.S. dollars. Even columns display values as a percent of first row in preceding column.

Tables 3 and 4 also underscore the prevalence of changes in HS codes over time. As of 2004, 49 percent of import products and 40 percent of export products had been involved in an HS code change. Moreover, trade in products with code changes accounted for 62 percent of the value of U.S. imports and 48 percent of the value of U.S. exports in 2004. Tracking changes in HS codes over time, therefore, is important in any empirical research using international trade data classified by HS codes, and critical when studying topics such as new product introduction.[8]

Section 6: Conclusion

This paper has presented an algorithm for concording ten-digit U.S. Harmonized System (HS) product codes over time and described how the algorithm can be used to create concordances with arbitrary beginning and end years. Furthermore, in summarizing the 1989 to 2004 concordance used in Bernard, Jensen, Redding and Schott (2009) it has illustrated the prevalence of changes in HS codes over time and the importance of tracking these changes when conducting empirical research in international trade.

A Appendix

This appendix provides Stata code that can be used to create HS concordances. It also describes the input and output files associated with this code and contained in the zip file hs_over_time_20090302.zip. The two sections of code below contain our algorithm for creating export and import HS concordances for arbitrary beginning and ending year-months between 1989 and 2007. Those comfortable with Stata programming should find it relatively easy to manipulate.

[8] We note that two features of Census' new-obsolete mappings complicate the identification of new product introductions (e.g., iPods). First, new HS codes always emerge from predecessor HS codes. Second, new HS codes' emergence may take place an unknown period of time after an underlying good has been introduced. Statistical agencies may wait to establish a new HS category until it reaches a certain size or until manufacturers apply sufficient lobbying.

Those unfamiliar with Stata programming can instead use one of the output files described below.

Each program requires as an input a data file containing the raw new-obsolete mappings discussed in the main text. These input files are named sch_b_concordances_20081101_02.dta and hts_concordances_20081101_02.dta, respectively, with the string after the "_" reflecting the version date of the file. The basic structure of these input files resembles the raw new-obsolete files, i.e., each set of obsolete HS codes is followed by the new set of HS codes into which they map. They are posted to the same website where this paper is found and contain the following variables:

- obsolete: old HS codes that become obsolete as of effective date;
- new: new HS codes associated with the obsolete codes;
- setyr: synthetic code to which new and obsolete codes belong, as defined in main text; and
- effyr: date the mapping is effective.

The first two sections of code below produce the output files that can be used to concord HS codes in U.S. import and export data, as demonstrated in the last section of this Appendix. Specifically, the code produces output files sch_b_concordances_VER_BEG_END.dta and hts_concordances_VER_BEG_END.dta, where VER, BEG and END reflect user-defined version dates (currently 20081101) and beginning-end years (exports:

1989_2007) or year-months (imports: 198906_200707), respectively. These concordances include the same variables as the input files, but with setyr and effyr standardized across family trees, as described in Section 4 above. Variables in the concordance output files include:

- obsolete: obsolete HS code;
- new: corresponding new HS code;
- setyr: synthetic code linking this mapping to all mappings in its family tree;
- effyr: year (export) or year-month (import) in which the particular new-obsolete mapping first appears in the raw data.

For those unfamiliar with Stata programming we also provide two additional output files in .txt format. These output files, named setyr_x_1989_2007.txt and setyr_m_1989_2007.txt, provide a record of every HS code associated with every setyr that appears in the 1989-2007 concorded data. The first column of each file lists the setyr's, sorted from low to high. Each additional column lists the actual HS codes appearing in a particular year of the trade data that should be replace by the setyr. These actual HS codes also are sorted from low to high in each year. To concord U.S. trade data from 1989 to 2007, one would just replace all codes listed in the table with the synthetic setyr, and then collapse the data according to these setyr's. HS codes not appearing in these output files are consistent across all years of the data.

A.1 Stata Code for Schedule B Concordance

**1 Preliminaries

```
clear
set more off
set mem 1000m
```

**2 Create a file that chains years together

** Note that to chain you have to always match later years to earlier years. That is the

** reason that the second loop below is nested.

** Note that you must set the local variables for the beginning and ending year you want,

** i.e., the long difference that you want to take; these locals govern both this and the ** next section.

```
local b  = 1989
local e  = 2007
local b1 = `b'+1
```

```
set more off
*quietly {

*chop up the data in the main file created above year and rename the vars for
*the merging to take place in the next loop
	forvalues y=`b'/`e' {
		use sch_b_concordances_20081101_02, clear
		keep if effyr==`y'
		rename new new`y'
		rename obsolete obs`y'
		rename setyr setyr`y'
		rename effyr effyr`y'
		order obs`y' new`y'
		sort obs`y'
		save temp_xchain_`y', replace
	}

*use the chopped up files from above to chain the obs-new matches across years.
* here, the goal is to find new's from subsequent years that modify new's
*from earlier years
```

*note that after the inside loop, which matches subsequent years to a given year, drop *observations unless they are chained, i.e., unless the merge code = 3

```
	forvalues s=`b'/`e' {
		use temp_xchain_`s', clear
		rename obs`s' obs
		forvalues t=`b'/`e' {
			if `t'>`s' {
				noisily display [`s'] " " [`t']
				rename new`s' obs`t'
				sort obs`t'
				joinby obs`t' using temp_xchain_`t',
unmatched(master)
				noisily tab _merge
				drop if _merge==2
				rename _merge _m`s'`t'
				rename obs`t' new`s'
			}
		}
		gen _mjunk=0
		egen idx = rowmax(_m*)
		noisily tab idx
```

```
            keep if idx==3
            sort obs
            drop _m*
            save temp2_xchain_`s', replace
      }
}
```

**3 Assign single setyear to all members of a family

**put the above chains, each of which starts with a different year from 1989 to 2007,

**back together into one file for the whole sample period;

**challenge here is to set a single setyr for all "families" revealed by the chain;

**note that there are two cases for a "family". in the first case, all members sprout from

**the same obsolete code in some year. in the second, two sub-families in an early year **are joined by a common code or set of codes in a subsequent year.

```
use temp2_xchain_`b', clear
forvalues y=`b1'/`e' {
      append using temp2_xchain_`y'
}
keep obs new* setyr* effyr*
```

```
capture duplicates drop

egen double setyr = rowmin(setyr*)

egen nchain = rownonmiss(new*)

rename obs obsolete

order obs setyr

sort obs

save temp2_xchain, replace


use temp2_xchain, clear

drop setyr effyr*

egen t1 = seq(), by(obs)

reshape long new setyr, i(obs t1) j(effyr)

drop if new==. & setyr==.

drop t1 nchain

duplicates drop obs effyr new setyr, force

egen osd=sd(setyr), by(obs)

egen nsd=sd(setyr), by(new)

sum nsd osd

drop osd nsd
```

*Now add back in the obsolete-new observations that are not part of chains. These come *from section 1

*have to add these in before the min loop below in case a non-chain obs-pair is part of a *family

```
sort obsolete new effyr
merge obsolete new effyr using sch_b_concordances_20081101_02
drop if effyr<`b' | effyr>`e'
tab _merge
drop _merge


*now start family identification loop
egen double t1     = min(setyr), by(obs)
rename setyr oldsetyr
local zzz = 2
local stop = 0
while `stop'==0 {
  quietly {
        noisily display [`zzz']
        local zlag = `zzz'-1
        if mod(`zzz',2)==0 {
              egen double t`zzz' = min(t`zlag'), by(new)
```

```
		}
		if mod(`zzz',2)~=0 {
			egen double t`zzz' = min(t`zlag'), by(obs)
		}
		compare t`zzz' t`zlag'
		gen idx = t`zzz'==t`zlag'
		tab idx
		local stop = r(r)==1
		local zzz = `zzz'+1
		display r(r) " " [`stop']
		drop idx
	}
}
local yyy = `zzz'-1
gen double setyr = t`yyy'
keep obs effyr new setyr
duplicates drop
sort obsolete new effyr
save  sch_b_concordances_20081101_`b'_`e', replace
!erase temp*.dta tn.dta to.dta sch_b*_01.dta sch_b*_02.dta
```

A2. Stata Code for HTS Concordance

**1 Preliminaries

clear

set more off

set mem 1000m

**2 Create a file that chains year-months together in order

** Note that to chain you have to always match later years to earlier years. That is the

** reason that the second loop below is nested.

** Note that you must set the local variables for the beginning and ending year you want,

** i.e., the long difference that you want to take; these locals govern both this and the

** next section.

local b = 1989.06

local e = 2007.07

local list1 = "1989.06 1989.07 1990.01 1990.05 1990.07 1990.08 1990.10 1991.01 1991.02 1991.05 1991.07 1992.01 1992.05 1992.07 1993.01 1993.02 1993.06

```
1993.07 1993.08 1993.11 1993.12 1994.01 1994.04 1994.06 1995.01 1995.07
1995.09 1996.01 1996.06 1996.07"
local list2 = "1996.11 1997.01 1997.02 1997.06 1997.07 1997.08 1998.01 1998.03
1998.04 1998.07 1998.08 1999.01 1999.07 2000.01 2000.03 2000.04 2000.07
2000.12 2001.01 2001.07 2002.01 2002.07 2002.08 2003.01 2003.02 2003.04
2003.07 2004.01 2004.02 2004.04"
local list3 = "2004.07 2005.01 2005.07 2005.11 2006.01 2006.03 2006.04 2006.06
2006.07 2007.01 2007.07"

set more off
quietly {

*chop up the data in the main file created above year and rename the vars for
*the merging to take place in the next loop; have to do this for every year-month
*because chains below need to start, iteratively, with each year-month
        foreach y in `list1' `list2' `list3' {
            noisily display [`y']
                local yn = int(`y'*100)
                use hts_concordances_20081101_02, clear
                keep if effyr==`y'
                rename new new`yn'
```

```
            rename obsolete obs`yn'

            rename setyr setyr`yn'

            rename effyr effyr`yn'

            order obs`yn' new`yn'

            sort obs`yn'

            save temp_xchain_`yn', replace

    }
```

*use the chopped up files from above to chain the obs-new matches across years.

* here, the goal is to find new's from subsequent years that modify new's from

*earlier years

*note that after the inside loop, which matches subsequent year-months to a given

*starting year-month,

*drop observations unless they are chained, i.e., unless the merge code = 3

```
    foreach s in `list1' `list2' `list3' {


    local sn = int(`s'*100)


  if `s'>=`b' & `s'<=`e' {

            use temp_xchain_`sn', clear

            rename obs`sn' obs
```

```
foreach t in `list1' `list2' `list3' {
    if `t'>`s' & `t'<=`e' {
        noisily display [`s'] " " [`t']
        local tn = int(`t'*100)
        rename new`sn' obs`tn'
        sort obs`tn'
        joinby obs`tn' using temp_xchain_`tn', unmatched(master)
        noisily tab _merge
        drop if _merge==2
        rename _merge _m`sn'`tn'
        rename obs`tn' new`sn'
    }
}
gen _mjunk=0
egen idx = rowmax(_m*)
noisily tab idx
keep if idx==3
sort obs
drop _m*
save temp2_xchain_`sn', replace
```

```
    }
  }
}

**3 Assign single setyear to all members of a family
**put the above chains, each of which starts with a different year from 1989 to 2004,
**back together into
**one file for the whole sample period;
**challenge here is to set a single setyr for all "families" revealed by the chain;
**note that there are two cases for a "family". in the first case, all members sprout from **the same obsolete
**code in some year. in the second, two sub-families in an early year are joined by a
**common code or set of codes
**in a subsequent year.
local b    = 1989.06
local e    = 2007.07
local b1   = 1989.01
local list1 = "1989.06 1989.07 1990.01 1990.05 1990.07 1990.08 1990.10 1991.01 1991.02 1991.05 1991.07 1992.01 1992.05 1992.07 1993.01 1993.02 1993.06 1993.07 1993.08 1993.11 1993.12 1994.01 1994.04 1994.06 1995.01 1995.07 1995.09 1996.01 1996.06 1996.07"
```

```
local list2 = "1996.11 1997.01 1997.02 1997.06 1997.07 1997.08 1998.01 1998.03
1998.04 1998.07 1998.08 1999.01 1999.07 2000.01 2000.03 2000.04 2000.07
2000.12 2001.01 2001.07 2002.01 2002.07 2002.08 2003.01 2003.02 2003.04
2003.07 2004.01 2004.02 2004.04"
local list3 = "2004.07 2005.01 2005.07 2005.11 2006.01 2006.03 2006.04 2006.06
2006.07 2007.01 2007.07"

local bn  = int(`b'*100)
local en  = int(`e'*100)
local b1n = int(`b1'*100)

use temp2_xchain_`bn', clear
foreach y in `list1' `list2' `list3' {
  if  `y'>`b' & `y'<=`e' {
        local yn  = int(`y'*100)
        display [`y']
        append using temp2_xchain_`yn'
  }
}
keep obs new* setyr* effyr*
capture duplicates drop
```

```
egen double setyr = rowmin(setyr*)

egen nchain = rownonmiss(new*)

rename obs obsolete

order obs setyr

sort obs

save temp2_xchain, replace


use temp2_xchain, clear

drop setyr effyr*

egen t1 = seq(), by(obs)

reshape long new setyr, i(obs t1) j(effyr)

rename effyr t2

gen double effyr = t2/100

drop if new==. & setyr==.

drop t1 nchain t2

duplicates drop

egen osd=sd(setyr), by(obs)

egen nsd=sd(setyr), by(new)

sum nsd osd

drop osd nsd
```

*Now add back in the obsolete-new observations that are not part of chains. These come *from section 1

*have to add these in before the min loop below in case a non-chain obs-pair is part of a *family

```
sort obsolete new effyr
merge obsolete new effyr using hts_concordances_20081101_02
drop if effyr<`b' | effyr>`e'
tab _merge
drop _merge


*now start family identification loop
egen double t1     = min(setyr), by(obs)
rename setyr oldsetyr
local zzz = 2
local stop = 0
while `stop'==0 {
  quietly {
          noisily display [`zzz']
          local zlag = `zzz'-1
          *mod(x,y) = x - y*int(x/y).
          if mod(`zzz',2)==0 {
```

```
			egen double t`zzz' = min(t`zlag'), by(new)
		}
		if mod(`zzz',2)~=0 {
			egen double t`zzz' = min(t`zlag'), by(obs)
		}
		compare t`zzz' t`zlag'
		gen idx = t`zzz'==t`zlag'
		tab idx
		local stop = r(r)==1
		local zzz = `zzz'+1
		noisily display r(r) " " [`stop']
		drop idx
	}
}
local yyy = `zzz'-1
gen double setyr = t`yyy'
keep obs effyr new setyr
rename effyr effyrmo
gen effyr = int(effyrmo)
duplicates drop
sort obsolete new effyrmo
```

```
save  hts_concordances_20081101_`bn'_`en', replace
!erase temp*.dta tn.dta to.dta hts*_01.dta hts*_02.dta
```

A3. Stata Code for Implementing Concordance in U.S. Trade Data

```
/*
Note that you must change the use and save commands below depending on whether
you are concording export or import data
*/

quietly {
forvalues y=1989/2004 {
local ylead = `y’+1
noisily display " "
noisily display " "
noisily display "NEW LOOP " [`y’]
noisily display " "
noisily display " "
*get obsolete-new files ready
*temp_obsolete is used to assign setyrs to codes that are last used in year y
*basically want to insure against the code ever becoming obsolete, i.e., it being
```

```
*an obsolete code in any year after the year of the loop
*note the input file varies depending on whether import or export data
*use sch_b_concordances_20081101_1989_2004, clear
use hts_concordances_20081101_1989_2004, clear
keep if effyr>=`ylead’
keep obsolete setyr
drop if obsolete==.
capture duplicates drop
sort obsolete
save temp_obsolete, replace
*temp_new is used to assign setyrs to codes that are new in year y
*bascially want to insure against this code ever having been a new code prior to this
*year; if so, need to assign it a setyr
*use sch_b_concordances_20081101_1989_2004, clear
use hts_concordances_20081101_1989_2004, clear
```

Concording U.S. HS Codes Over Time 18

```
keep if effyr<=`ylong’
keep new setyr
drop if new==.
duplicates drop
sort new
```

```
save temp_new, replace
*read in data and collapse to appropriate level
*assume trade file is called exports_Y or imports_Y, where Y=year
*assume file contains v=value, hs1=hs code, country1=us country code,
*year and month
*use exports_`y’, clear
use imports_`y’, clear
rename all_val_yr v
destring commodity, force g(hs1)
gen year = `y’
gen month = int(uniform()*12) + 1
gen rp = uniform()>0.5
destring cty_code, force g(country1)
gen alpha1 = 1
collapse (sum) v, by(hs1 country1 month year)
format hs1 %15.0f
*merge in obsolete-code family identifiers
rename hs1 obsolete
sort obsolete
merge obsolete using temp_obsolete, keep(setyr)
noisily tab _merge
```

```
drop if _merge==2

drop _merge

rename obsolete hs1

*merge in new-code family identifiers

rename hs1 new

sort new

merge new using temp_new, keep(setyr) update

noisily tab _merge

drop if _merge==2

drop _merge

save exports_`y'_concorded_precollapse, clear

save imports_`y'_concorded_precollapse, clear

rename new hs1

*resent hs codes to family identifiers where appropriate

replace hs1=setyr if setyr~=.

collapse (sum) v, by(hs1 country1 month year)

*save exports_`y'_concorded, replace

save imports_`y'_concorded, replace

}

}
```

```
*create files matching actual codes to setyrs by year
forvalues y=1989/2004 {
*use exports_`y'_concorded_precollapse, replace
use imports_`y'_concorded_precollapse, replace
rename hs1 hs`y'
drop v
drop if setyr==.
sort setyr hs`y'
*save junk_x_`y', replace
save junk_m_`y', replace
}
*use junk_x_1989, replace
use junk_m_1989, replace
forvalues y=1990/2004 {
display [`y']
*merge setyr using junk_x_`y'
merge setyr using junk_m_`y'
tab _merge
drop _merge
order setyr
sort setyr hs`y'
```

```
}
forvalues y=1989/2004 {
egen i`y'= tag(setyr hs`y')
replace hs`y'=. if i`y'==0
drop i`y'
}
*now sort each column within setyr
egen xx = seq()
drop xx
reshape long hs, i(xx setyr) j(year)
sort year setyr hs
drop xx
egen xx = seq(), by(year)
reshape wide hs, i(xx setyr) j(year)
drop xx
*save setyr_x_1989_2004, replace
save setyr_m_1989_2004, replace
```

Bibliography

Amiti, Mary and Jozef Konings (2007), "Trade Liberalization, Intermediate Inputs and Productivity: Evidence from Indonesia," *American Economic Review*, 97, pp. 1611-1638.

Aw, Bee Yan, Xiaomin Chen and Mark J. Roberts (2001), "Firm-Level Evidence on Productivity Differentials and Turnover in Taiwanese Manufacturing," *Journal of Development Economics*, 66, pp. 51-86.

Aw, B.Y., Chung, S. and Mark Roberts (2000), "Productivity and Turnover in the Export Market: Micro-Level Evidence from Korea and Taiwan (China)," *World Bank Economic Review*, 14, pp. 65-90

Baldwin, John R. and Paul K. Gorecki (1986), *The Role of Scale in Canada-U.S. Productivity Differences in the Manufacturing Sector*, University of Toronto Press.

Bartelsman, Eric J., Randy A. Becker and Wayne B. Gray (2000) "NBER-CES Manufacturing Industry Database," NBER Technical Working Paper 205.

Bernard, Andrew B., J. Bradford Jensen, Stephen J. Redding and Peter K. Schott (2009), "The Margins of U.S. Trade (Long Version)," NBER Working Paper 14662.

Bernard, Andrew, Stephen Redding and Peter Schott (2009), "Multi-Product Firms and Product-Switching," *American Economic Review*, forthcoming.

Bernard, Andrew, J. Bradford Jensen and Peter Schott (2006), "Trade Costs, Firms and Productivity," *Journal of Monetary Economics*, 53, pp. 917-937.

Bernard, Andrew, Stephen Redding and Peter Schott (2006), "Multi-Product Firms and Trade Liberalization," mimeo.

Bernard, Andrew, Jonathan Eaton, J. Bradford Jensen and Samuel Kortum (2003), "Plants and Productivity in International Trade," *American Economic Review*, 93, pp. 1268-1290.

Bernard, Andrew and Joachim Wagner (2001), "Export Entry and Exit by German Firms," *Review of World Economics*, 137(1), pp. 105-23.

Bernard, Andrew and J. Bradford Jensen (1999), "Exceptional Exporter Performance: Cause, Effect, or Both?," *Journal of International Economics*, 47, pp. 1-25.

Blonigen, Bruce and Jee-Hyeong Park (2004), "Dynamic Pricing in the Presence of Antidumping Policy: Theory and Evidence," *American Economic Review*, 94, pp.134-154.

Bown, Chad (2007), "Global Antidumping Database 3.0," mimeo.

Campbell, Neil and Neil Vousden (1994), "The Organizational Cost of Protection," *Journal of International Economics,"* 37 (3-4), pp. 219-238.

Chang, Pao-Li (2005), "Protection for Sale Under Monopolistic Competition," *Journal of International Economics*, *66*(2), pp. 509-26.

Caves, Douglas W., Laurits R. Christensen and W. Erwin Diewert (1982), "The Economic Theory of Index Numbers and the Measurement of Input, Output and Productivity," *Econometrica*, 50(6), pp. 1393-1414.

Crowley, Meredith (2006), "Do Antidumping Duties and Safeguard Tariffs Open or Close Technology Gaps?," *Journal of International Economics*, 68, pp. 469-484.

Dixit, Avinash and Joseph Stiglitz (1977), "Monopolistic Competition and Optimum Product Diversity," *The American Economic Review*, *67*, pp. 297-308.

Ethier, Wilfred (1982), "National and International Returns to Scale in the Modern Theory of International Trade," *The American Economic Review*, *72*, 389-405.

Fernandes, Ana (2007), "Trade Policy, Trade Volumes and Plant-Level Productivity in Colombian Manufacturing Industries," *Journal of International Economics*, 71(1), pp. 52-71.

Feenstra, Robert, John Romalis and Peter Schott (2002), "U.S. Imports, Exports and Tariff Data," NBER Working Paper # 9387.

Feenstra, Robert C., James R. Markusen and William Zeile (1992), "Accounting for Growth with New Inputs: Theory and Evidence," *The American Economic Review*, *82*(2), pp. 415-21.

Goh, A.-T. (2000), "Opportunity Cost, Trade Policies and the Efficiency of Firms," *Journal of Development Economics*, 62, pp. 363–383.

Grossman, Gene and Elhanan Helpman (1994), “Protection for Sale,” *The American Economic Review*, *84*, pp. 833-50.

Holmes, T. and J. Schmitz (2001), “A Gain From Trade: From Unproductive to Productive Entrepreneurship,” *Journal of Monetary Economics*, 47(2), pp. 417-46.

Konings, Jozef and Hylke Vandenbussche (2008), “Heterogeneous Responses of Firms to Trade Protection,” *Journal of International Economics*, 76, pp. 371-383.

Konings, Jozef and Hylke Vandenbussche (2005), “Antidumping Protection and Markups of Domestic Firms: Evidence from Firm Level Data,” *Journal of International Economics*, 65, pp. 151-165.

Krugman, Paul R (1979) “Increasing Returns, Monopolistic Competition and International Trade,” *Journal of International Economics*, *9*, 469-479.

Levinsohn, James and Amil Petrin (2003), “Estimating Production Functions Using Intermediates to Control for Unobservables,” *Review of Economic Studies*, 70, pp. 317-341.

Matsuyama, Kiminori (1990), “Perfect Equilibria in a Trade Liberalization Game,” *American Economic Review*, 80(3), pp. 480-492.

Melitz, Marc J. (2003), “The Impact of Trade on Aggregate Industry Productivity and Intra-Industry Reallocations.” *Econometrica*, 71(6), pp. 1695-725.

Miyagiwa, Kaz and Yuka Ohno (1995), "Closing the Technology Gap Under Protection," *American Economic Review*, 85(4), pp. 755-770.

Miyagiwa, Kaz and Yuka Ohno (1999), "Credibility of Protection and Incentives to Innovate," *International Economic Review*, 40(1), pp. 143-163.

Muendler, Marc-Andreas (2004), "Trade, Technology, and Productivity: A Study of Brazilian Manufacturers," mimeo.

Pavcnik, Nina (2002), "Trade Liberalization, Exit and Productivity Improvements: Evidence from Chilean Plants." *Review of Economic Studies*, *69*(1), pp. 245-76.

Ratnayake, Ravi (1999), "Industry Concentration and Competition: New Zealand Experience." *International Journal of Industrial Organization*, 17, 1041-1057.

Rodrik, Dani (1992), "Closing the Productivity Gap: Does Trade Liberalization Really Help," In: Helleiner, G., ed., *Trade Policy, Industrialization and Development*, Clarendon Press.

Roberts, Mark J (1996), "Colombia, 1977-85: Producer Turnover, Margins, and Trade Exposure," in Mark J. Roberts and James R. Tybout (eds.), *Industrial Evolution in Developing Countries: Micro Patterns of Turnover, Productivity, and Market Structure*, Oxford University Press, pp. 227-59.

Schor, Adriana (2004), "Heterogeneous Productivity Response to Tariff Reduction: Evidence from Brazilian Manufacturing Firms," NBER Working Paper 10544.

Serti, Francesco and Chiara Tomasi (2007), "Self Selection and Post-Entry Effects of Exports. Evidence from Italian Firms," mimeo.

Tybout, James (2001), "Plant- and Firm-Level Evidence on 'New' Trade Theories," NBER Working Paper 8418.

Tybout, James and M. D. Westbrook (1995), "Trade Liberalization and the Dimension of Efficiency Change in Mexican Manufacturing Industries," *Journal of International Economics*, *39*(1-2), pp. 53-78.

United States International Trade Commission (2006), "Import Injury Investigations: Case Statistics: FY 1980-2005."

Van Biesebroeck, Johannes (2004), "Robustness of Productivity Estimates," National Bureau of Economic Research Working Paper 10303.