PRODUCT DIFFERENTIATION, MULTI-PRODUCT FIRMS AND ESTIMATING
THE IMPACT OF TRADE LIBERALIZATION ON PRODUCTIVITY

Jan De Loecker

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ABSTRACT

In this paper I analyze the productivity gains from trade liberalization in the Belgian textile industry.
So far, empirical research has established a strong relationship between opening up to trade and productivity,
relying almost entirely on deflated sales to proxy for output in the production function. The latter implies
that the resulting productivity estimates still capture price and demand shocks which are most likely
to be correlated with the change in the operating environment, which invalidate the evaluation of the
welfare implications. In order to get at the true productivity gains I propose a simple methodology
to estimate a production function controlling for unobserved prices by introducing an explicit demand
system. I combine a unique data set containing matched plant-level and product-level information
with detailed product-level quota protection information to recover estimates for productivity as well
as parameters of the demand side (markups). I find that when correcting for unobserved prices and
demand shocks, the estimated productivity gains from relaxing protection are only half (from 8 to
only 4 percent) of those obtained with standard techniques.

Jan De Loecker
Stern School of Business
New York University
44 West Fourth Street
New York, NY 10012
and NBER
jdl16@nyu.edu

1 Introduction

Over the last years a large body of empirical work has emerged that relies on the estimation of production functions to evaluate the impact of policy changes on the efficiency of producers and the industry as a whole. The reason for this is at least twofold. First of all, there is a great interest in evaluating active policy changes such as trade liberalization, deregulation and privatization of industries. One of the questions that typically arise is whether the policy change had any impact on the efficiency of firms in the economy. It is in this context that the ability to estimate a production function using micro data (firm-level) is important as it allows us to recover a *measure* for (firm-level) productivity and relate this to changes in the operating environment. Secondly, the increased availability of firm-level datasets for various countries and industries has further boosted empirical work analyzing productivity dynamics. Out of these set of papers, a robust result is that periods of changes in the competitive environment of firms - like trade liberalization - are associated with *measured productivity gains* and that firms engaged in international trade (through export or FDI) have higher measured productivity.[1]

The *productivity measures* that are used to come to these conclusions are, however, recovered after estimating (some form of) a sales generating production function where output is replaced by sales. The standard approach has been to use the price index - of a given industry - to proxy for these unobserved prices. The use of the price index is only valid if all firms in the industry face the same output price and corresponds with the assumption that firms produce homogeneous products and face a common and *infinite price elasticity of demand* (Melitz, 2001). In the case of differentiated products this implies that the estimates of the input coefficients are biased and in addition lead to productivity estimates that capture markups and demand shocks.[2] In a second step these productivity estimates are then regressed on variables of interest, say the level of trade protection or tariffs. This implies that the impact on *actual productivity* cannot be identified - using a two-step procedure - which invalidates evaluation of the welfare implications.

In this paper I analyze the productivity gains from trade liberalization in the Belgian textile industry. As in most empirical work that has addressed similar questions, I do not observe output at the firm level and therefore unobserved prices and demand shocks need to be controlled for. In order to answer this question, I first introduce a simple methodology for getting reliable estimates of productivity in an environment of imperfect competition in the product market where I allow for multi-product firms. The estimation strategy is related to the original work of Klette and Griliches (1996) where the bias of production function coefficients due to using deflated firm-level sales (based on an industry-wide producer price index) to proxy for firm-level

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[1] Pavcnik (2002) documents the productivity gains from trade liberalization in Chile, Smarzynska (2004) finds positive spillovers from FDI in Lithuania and Van Biesebroeck (2005) finds learning by exporting in Sub-Saharan African manufacturing. Olley and Pakes (1996) analyze the productivity gains from deregulating the US telecom equipment industry.

[2] Obtaining precise productivity estimates by filtering out price and demand shocks has a wide range of implications for other applied fields. For instance in applying recently developed methods to estimate dynamic (oligopoly) games where productivity is a key primitive (Collard-Wexler 2006).

output is discussed. In their application the interest lies in recovering reliable estimates for returns to scale and not in productivity estimates per se. At the same time a literature emerged trying to correct for the simultaneity bias without relying on instruments in order to recover reliable estimates for productivity. The latter is a well documented problem when estimating a production function with OLS that inputs are likely to be correlated with unobserved productivity shocks and therefore lead to biased estimates of the production function. Olley and Pakes (1996) introduced an empirical strategy based on a theoretical dynamic optimization problem of the firm under uncertainty where essentially unobserved productivity in the production function is replaced with a polynomial in investment and capital. A series of papers used this approach to verify the productivity gains from changes in the operating environment of firms such as trade liberalization, trade protection among others. In almost all of the empirical applications the omitted price variable bias was ignored or assumed away.[3] In this paper I analyze productivity dynamics during a period of trade liberalization while correcting both for the omitted price variable and the simultaneity bias. I use the Olley and Pakes (1996) procedure to control for the simultaneity bias and their framework turns out to be very instructive to evaluate the importance of demand shocks in the production function and how they affect the productivity estimates.[4] In addition, to correct for the *omitted price variable bias* and obtain unbiased coefficients of the production function, I introduce a rich source of product-level data matched to the production dataset. This unique additional piece of information allows me to introduce a richer demand system and recover markup estimates in addition to estimates for productivity which are the ultimate goal. I empirically show that the traditional 'productivity measures' still capture price and demand shocks which are likely to be correlated with the change in the operating environment.

I find that in my data the omitted price variable bias works in the opposite way and matters more than the simultaneity and the selection bias. An important implication is that my estimates for returns to scale are significantly higher than one.[5] Furthermore, my results suggest that only half of the measured productivity gains established using standard techniques capture true productivity gains. The estimated productivity gains from relaxing quota protection are (on average) 4 percent in contrast to 8 percent when we ignore the fact that firm-level revenue captures variation in prices as well.

My framework suggests that the channel through which trade liberalization impacts productivity is mostly by cutting off the inefficient producers from the productivity distribution and therefore increases the average productivity of the industry. However, the (within-firm)

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[3]Some authors did explicitly reinterpret the productivity measures as sales per input measures. For instance see footnote 3 on page 1264 of Olley and Pakes (1996).

[4]This does not rule out the use of alternative proxy estimators such as the estimator suggested by Levinsohn and Petrin (2003), however, with some additional assumptions made on the relation between the unobserved productivity shocks and markups. See Appendix C for a discussion on this.

[5]It is actually quite surprising that in recent papers relying on various proxy estimators to control for the simultaneity bias, almost no increasing returns to scale are established for those industries with high fixed costs where we would expect to find them.

productivity gains for those producers that remain active are small and sometimes even negligible. These two observations then imply a very different interpretation of how opening up trade impacts individual firms. Furthermore, the reallocation of activities across surviving firms is not as closely tied to productivity, but rather an interplay of the ability to markup over costs and productivity.

Combing a production function and a demand system into one framework provides other interesting results and insights with respect to the product mix and market power. I find that including the product mix of a firm is an important dimension to consider when analyzing productivity dynamics. Even if this has no impact on the aggregation of production across products, it matters since it allows to estimate different markups across product segments. In the context of the estimation of production functions multi-product firms have not received a lot of attention with the exception of the theoretical work of Melitz (2001). The main reason for this is the lack of detailed product-level production data: inputs (labor, material and capital) usage and output by product and firm. Ignoring the product-level dimension has some important implications on the production technology we assume, i.e. no cost synergies or economies of scope are allowed. In my data I only observe the number of products produced per firm and where these products are located in product space (segments of the industry). This does not allow me to depart from the standard modeling assumptions on the production side as in Melitz (2001). But it does allow me to specify a richer demand system and therefore enables me to investigate the productivity response controlling for price and markup effects. For the latter it is crucial to introduce products as the quota protection that are used at the EU level vary greatly across product categories. This however does not capture the channel recently described by Bernard et. *al* (2003). They document the importance of product mix variation across producers in a given industry and how firms respond to shocks (trade liberalization) along this dimension.[6]

A growing number of papers have studied the impact of various trade policy changes on productivity in the absence of market power.[7] By introducing a rich source of demand variation I am able to decompose the traditional measured productivity gains into real productivity gains and demand side related components and evaluate whether opening up to trade is truly changing the efficiency of producers. In addition, the method sheds light on other parameters of interest such as markups. I estimate markups ranging from 0.16 for the interior segment to 0.23 in the clothing segment of the textile industry. These numbers are in line with what other studies have found relying on different methods. In the context of trade liberalization, a number of authors have found strong relationships between trade protection and markups (Konings and Vandenbussche, 2005). My results therefore shed light on the importance of both the productivity and markup response to a change in a trade regime.

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[6] These authors define a product as a 5 digit industry code which is a product line. I refer to a product as an 8 digit product code which implies that we expect to see - if anything - bigger numbers on for instance the number of products per firm.

[7] See Tybout (2000) for a review on the relationship between openness and productivity in developing countries.

Recent work has discussed the potential bias of ignoring demand shocks when estimating production functions based on deflated firm-level sales to proxy for output. Katayama et al. (2003) start out from a nested logit demand structure and verify the impact of integrating a demand side on the interpretation of productivity. Melitz and Levinsohn (2002) assume a representative consumer with Dixit-Stiglitz preferences and they feed this through the Levinsohn and Petrin (2003) estimation algorithm.[8] Foster, Haltiwanger and Syverson (forthcoming) discuss the relation between physical output, revenue and firm-level prices. They study this in the context of market selection and they state that productivity based upon physical quantities is negatively correlated with establishment-level prices while productivity based upon deflated revenue is positively correlated with establishment-level prices. The few papers that explicitly analyze the demand side when estimating productivity or that come up with a strategy to do so all point in the same direction: estimated productivity still captures demand related shocks.[9]

The remainder of this paper is organized as follows. In section 2 the standard approach to estimate production functions is discussed and I introduce a demand system and show the bias on the production function coefficients. Section 3 introduces the estimation strategy and the potential bias of using standard productivity estimates to evaluate policy changes. In section 4, I present the data that includes detailed product-level information in addition to a rich firm-level dataset of Belgian textile producers. In section 5 I present the coefficients of the production functions as well as the estimated parameters of the demand system. In section 6 I analyze the effects of the trade liberalization episode in the EU textiles on productivity, where the trade liberalization is measured by the drastic fall in product specific quota protection. The quota information also serves as an important *control variable* for the unobserved prices through the introduction of the demand system. The last section concludes.

2   Estimating productivity using production data

I briefly review the traditional problems one runs into when estimating a production function using typical production data on revenue and various inputs of a sample of firms. Given the focus is on controlling for unobserved firm specific prices and demand shocks, I will discuss the advantages of specifying an explicit demand system in more detail. Finally, I show how having information on the product mix of firms allows me to estimate a less restrictive substitution pattern across the products of the industry.

2.1   Identification of the production function parameters

Let us start with the production side where a firm i at time t produces (a product) according to the following production function

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[8] I will come back to the exact differences and extensions of my methodology compared to Melitz (2001) and Levinsohn and Melitz (2002) theoretical setup.

[9] See Bartelsman and Doms (2000) for a comprehensive review on recent productivity studies using micro data. Concerning the topic of this paper I refer to page 592.

$$Q_{it} = L_{it}^{\alpha_l} M_{it}^{\alpha_m} K_{it}^{\alpha_k} \exp(\alpha_0 + \omega_{it} + u_{it}^q) \tag{1}$$

where Q_{it} stands for the quantity produced, L_{it}, M_{it} and K_{it} are the three inputs labor, materials and capital; and α_l, α_m and α_k are the coefficients, respectively.[10] The constant term α_0 captures the mean productivity and γ captures the economies of scale, i.e. $\gamma = (\alpha_l + \alpha_m + \alpha_k)$. Productivity is denoted by ω_{it} and u_{it}^q is an $i.i.d.$ component.

The standard approach in identifying the production function coefficients starts out with a production function as described in equation (1). The physical output Q_{it} is then substituted by deflated revenue $(\widetilde{R}_{it})$ using an industry price deflator (P_{It}). Taking logs of equation (1) and relating it to the (log of) observed revenue per firm $r_{it} = q_{it} + p_{it}$, we get the following regression equation

$$r_{it} = x_{it}\alpha + \omega_{it} + u_{it}^q + p_{it} \tag{2}$$

where $x_{it}\alpha = \alpha_0 + \alpha_l l_{it} + \alpha_m m_{it} + \alpha_k k_{it}$. The next step is to use the industry wide price index p_{It} and subtract it from both sides to take care of the unobserved firm-level price p_{it}.

$$\widetilde{r}_{it} = r_{it} - p_{It} = x_{it}\alpha + \omega_{it} + (p_{it} - p_{It}) + u_{it}^q \tag{3}$$

Most of the literature on the estimation of productivity has worried about the correlation between the chosen inputs x_{it} and the unobserved productivity shock ω_{it}. The coefficient on the freely chosen variables labor and material inputs will be biased upwards as a positive productivity shock leads to higher labor and material usage $(E(x_{it}\omega_{it}) > 0)$.

Even if this is corrected for, from equation (3) it is clear that if firms produce differentiated products or have some pricing power the estimates of α will be biased. As mentioned in Klette and Griliches (1996) inputs are likely to be correlated with the price a firm charges.[11] The error term $(u_{it}^q + p_{it} - p_{It})$ still captures firm-level price deviation from the average (price index) price used to deflate the firm-level revenues. Essentially, any price variation (at the firm level) that is correlated with the inputs biases the coefficients of interest (α) as $E(x_{it}(p_{it} - p_{It})) \neq 0$. The sign of the bias could go either way as it depends on the correlation between the price a firm charges and the level of its inputs which works through the output of a firm. Therefore firm-level inputs (materials and labor) are correlated with the unobserved price and thus under- or overestimates the coefficients on labor and materials. This is referred to as the omitted price variable bias. Another source of bias is introduced by unobserved demand shocks that might lead to a higher price and induces a correlation between inputs and price.

The omitted price bias might work in the opposite direction as the simultaneity bias - the correlation between the unobserved productivity shock (ω_{it}) and the inputs (x_{it}) - making any

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[10] The Cobb-Douglas production function assumes a substitution elasticity of 1 between the inputs. The remainder of the paper does not depend on this specific functional form. One can assume e.g. a translog production function and proceed as suggested below.

[11] The interpretation of the correlation is somewhat different here since my model is estimated in log levels and not in growth rates as in Klette and Griliches (1996).

prior on the total direction of the bias hard. It is also clear that even when the marginal product of the inputs (α) are not of interest, the productivity estimate is misleading as it still captures price and consequently demand shocks.

The same kind of reasoning can be followed with respect to the measurement of material inputs where often a industry wide material price deflator is used to deflate firm-level cost of materials. However, controlling for unobserved prices takes - at least partly - care of this. The intuition is that if material prices are firm specific, a higher material price will be passed through a higher output price if output markets are imperfect, the extent of this pass through depends on the relevant markup. The only case where this reasoning might break down is when input markets are imperfect and output markets are perfectly competitive, which is not a very likely setup.[12]

2.2   Introducing demand and product differentiation

I now introduce the demand system that firms face in the output market. Firms are assumed to operate in an industry characterized by horizontal product differentiation, where η captures the substitution elasticity among the different products in a segment and η is finite. As mentioned in Klette and Griliches (1996) similar demand systems have been used extensively under the label of Dixit-Stiglitz demand. The key feature is that monopolistic competition leads to price elasticities which are constant and independent of the number of varieties.[13] In addition, I explicitly introduce unobserved demand shocks that are allowed to be correlated with price and other demand conditions. In the empirical application I will use product-firm dummies and product specific quota restrictions as additional controls.

The introduction of an explicit demand side into the revenue production function is very closely related to the model of Melitz and Levinsohn (2002) and Klette and Griliches (1996). However, there are some important differences and extensions I suggest. Firstly, in addition to the plant-level dataset I will introduce product-level information matched to the plants allowing me to put more structure on the demand side. They proxy the number of products per firm by the number of firms in an industry, while I observe the actual number of products produced by each firm and additional demand related variables. I use this additional source of variation to identify the elasticity of substitution for different segments of the industry. Secondly, aside from a discussion of the methodology, I empirically show the bias in the production function coefficients and in the resulting productivity estimates. Finally, I use segment demand shifts, product dummies and product specific quota restrictions to further *instrument* for demand

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[12] If material prices differ across firms, an additional correlation of the input with the unobserved price p_i is introduced through the correlation between output prices p_i and material prices p_i^m. Note that this is in addition to the correlation between material m_i used and prices p_i.This follows from the fact that deflated material costs can be written as $(m_i + p_i^m - p_I^m)$.

[13] The choice of this conditional demand system does not rule out other specifications to be used in the remainder of the paper. However, it implies that the inverse of the elasticity of substitution (demand) is the relevant markup as the substitution elasticity with respect to other goods (non textile products) is zero.

shocks to obtain consistent estimates of the supply side parameters as they provide an exogenous source of demand side shifts. I rely on my estimates to analyze the potential (within-firm) productivity gains from the trade liberalization episode in the EU textile industry. The structure of the demand system I build on implies that all unobserved demand shocks shift the individual firm's demand intercept around.

It is clear that the demand system is quite restrictive and implies one single elasticity of substitution for all products within a given product range - *segment* - and hence no differences in cross price elasticities. In the empirical application the elasticity of substitution is allowed to differ among product segments. This is in contrast to the commonly used (implicit) assumption that all firms face *one infinite price elasticity of demand*. The motivation for modeling demand explicitly here is to control for unobserved price variation. However the final interest lies in an estimate of productivity and further relaxing the substitution patterns here would just reinforce the argument.

The choice of demand system needed to identify the parameters of interest is somewhat limited due to missing demand data, i.e. prices and quantities. Therefore, one has to be willing to put somewhat more structure on the nature of demand. However, the modeling approach here does not restrict any demand system as long as the inverse demand system can generate a (log-) linear relationship of prices and quantities.

I start out with single product firms and show how this leads to my augmented production function. In a second step I allow for firms to produce multiple products. The focus is on the resulting productivity estimates and in the case of multi-product firms these can be interpreted as average productivity across a firm's products.

2.2.1 A Simple Demand Structure: Single Product Firms

I follow Klette and Griliches (1996) and later on I extend it by allowing firms to produce multiple products. I start out wit a simple (conditional) demand system where each firm i produces a single product and faces the following demand Q_{it}

$$Q_{it} = Q_{It} \left(\frac{P_{it}}{P_{It}} \right)^{\eta} \exp(u_{it}^d + \xi_{it}) \tag{4}$$

where Q_{It} is an aggregate demand shifter and here directly relates to the industry output at time t. As noted by Klette and Griliches (1996) this industry output can easily be computed using firm-level revenues and the producer price index of the industry.[14] Industry output Q_{It} is simply a weighted average of the deflated revenues $Q_{It} = (\sum_i^N ms_{it} R_{it})/P_{It}$ where the weights (ms_{it}) are the market shares. This observation is important for the empirical analysis where I will use this notion to construct *segment-specific output* (demand shifters) using firm-specific product mix information. (P_{it}/P_{It}) is the relative price of firm i with respect to the average price

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[14]This comes from the observation that a price index is essentially a weighted average of firm-level prices where weights are market shares (see Appendix A.2). Under the given demand structure it follows that (the first order proxy for) the price index is a market share weighted average of the firm-level prices.

in the industry, u_{it}^d is an idiosyncratic shock specific to firm i and η is the substitution elasticity between the differentiated products in the industry, where $-\infty < \eta < -1$. As mentioned above, I allow for unobserved demand shocks ξ_{it} to be correlated with price and the observed demand shifters. In discrete choice models like Berry (1994) and Berry, Levinsohn and Pakes (1995) where observed product characteristics are introduced this unobserved demand shock ξ_{it} is interpreted as (product) quality.

Taking logs of equation (4) and writing the price as a function of the other variables results in the following expression where $x_{it} = \ln X_{it}$

$$p_{it} = \frac{1}{\eta}(q_{it} - q_{It} - u_{it}^d - \xi_{it}) + p_{It} \tag{5}$$

As discussed extensively in Klette and Griliches (1996) and Melitz and Levinsohn (2002), the typical firm-level dataset has no information on physical output per firm and prices.[15] Commonly, we only observe revenue and we deflate this using an industry-wide deflator. The observed revenue r_{it} is then substituted for the true output q_{it} when estimating the production function. I now substitute expression (5) for the price p_{it} in equation (2) to get an expression for revenue. From here forward, I consider deflated revenue ($\tilde{r}_{it} = r_{it} - p_{It}$)

$$\tilde{r}_{it} = r_{it} - p_{It} = \left(\frac{\eta+1}{\eta}\right)q_{it} - \frac{1}{\eta}q_{It} - \frac{1}{\eta}(u_{it}^d + \xi_{it}) \tag{6}$$

Now I only have to plug in the production technology as expressed in equation (1) and I have a revenue generating production function with both demand and supply variables and parameters.

$$\tilde{r}_{it} = \left(\frac{\eta+1}{\eta}\right)(\alpha_0 + \alpha_l l_{it} + \alpha_m\, m_{it} + \alpha_k k_{it}) - \frac{1}{\eta}q_{It} + \left(\frac{\eta+1}{\eta}\right)(\omega_{it} + u_{it}^q) - \frac{1}{\eta}(u_{it}^d + \xi_{it})$$

It is clear that if one does not take into account the degree of competition on the output market (firm price variation), that the analysis will be plagued by an omitted price variable bias and the estimated coefficients are estimates of a reduced form combining the demand and supply side in one equation. This leads to my general estimating equation of the revenue production function

$$\tilde{r}_{it} = \beta_0 + \beta_l l_{it} + \beta_m\, m_{it} + \beta_k k_{it} + \beta_\eta q_{It} + (\omega_{it}^* + \xi_{it}^*) + u_{it} \tag{7}$$

where $\beta_h = ((\eta+1)/\eta)\alpha_h$ with $h = l, m, k$; $\beta_\eta = -\eta^{-1}$, $\omega_{it}^* = ((\eta+1)/\eta)\omega_{it}$, $\xi_{it}^* = -\eta^{-1}\xi_{it}$ and $u_{it} = ((\eta+1)/\eta)u_{it}^q - \frac{1}{\eta}u_{it}^d$. When estimating this equation (7) I recover the production function coefficients $(\alpha_l, \alpha_m, \alpha_k)$ and returns to scale parameter (γ) controlling for the omitted price variable and the simultaneity bias, as well as an estimate for the elasticity of substitution η. In fact, to obtain the true production function coefficients (α) I have to multiply the estimated reduced form parameters (β) by the relevant markup $(\frac{\eta}{\eta+1})$. When correcting for the simultaneity

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[15]Exceptions are Dunne and Roberts (1992), Jaumandreu and Mairesse (2004), Eslava et al.(2004) and Foster et al. (2005) where plant-level prices are observed and thus demand and productivity shocks can be estimated separately. To my knowledge this is a very rare setup.

bias I follow the Olley and Pakes (1996) procedure and replace the productivity shock ω_{it} by a function in capital and investment.

In my empirical analysis I will estimate various versions of (7) as the product information linked to every firm allows me to put more structure on the demand side, e.g. allowing the demand elasticity to vary across different segments and proxy for unobserved demand shocks (ξ_{it}) using product dummies. Adding the extra information from the product space is not expected to change the estimated reduced form coefficients (β), but it will have an impact on the estimated demand parameter η and hence on the true production function coefficients (α).[16]

2.2.2 Multi-product firms

I now allow firms to produce multiple products and the demand system is identical to the one expressed in equation (4), only a product subscript j is added. Note that the demand is now relevant at the product level. There are N firms and M products in the industry with each firm producing M_i products, where $M = \sum_i M_i$.[17] I divide the industry into S segments that each capture a part of the various products in the industry and I allow for segment specific price elasticities of demand. In the single product case the demand system is the same for every firm i, whereas in the multiple product case the demand is with respect to product j of firm i.

$$Q_{ijt} = Q_{Ist} \left(\frac{P_{ijt}}{P_{Ist}} \right)^{\eta_s} \exp(u_{ijt}^d + \xi_{ijt}) \tag{8}$$

The demand for product j of firm i is given by Q_{ijt}, Q_{Ist} is the demand shifter relevant at the product-level, P_{Ist} is the industry price index relevant at the product level, η_s is the demand elasticity relevant at the segment level, ξ_{ijt} is unobserved demand shock at the product level (e.g. quality) and u_{ijt}^d is product j specific idiosyncratic shock.[18] Note that the unobserved demand shock now has subscript j and as I will argue later in the case that it is only product specific $\xi_{ijt} = \xi_j$, having information on the products a firm produces is sufficient to control for the cross sectional variation. The elasticity of demand η_s is now specific to a given product segment s of the industry.

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[16] The setup is similar to the approach taken by Klette and Griliches (1996). However, three main problems remain unchallenged in their method, which are largely recognized by the authors. Firstly, industry output might proxy for other omitted variables relevant at the industry level such as industry wide productivity growth and factor utilization. The constant term and the residual in their model should take care of it since time dummies are no longer an option as they would take all the variation of the industry output. I use additional demand variables to control for demand shocks not picked up by industry output. Secondly, the residual still captures the unobserved productivity shock and biases the estimates on the inputs. I proxy for this unobserved productivity shock using the method suggested by Olley and Pakes (1996) to overcome the simultaneity bias, i.e. by introducing a polynomial in investment and capital. The third problem is closely related to the solution of the simultaneity problem. Klette and Griliches (1996) end up with a negative capital coefficient partly due to estimating their production function in growth rates.

[17] In the empirical application, I have 308 (N) firm observations and 2,990 firm-product (M) observations, with 563 unique product categories (j).

[18] In the multi-product model I have to aggregate the revenues per product to the firm's total revenue. The demand shifters are thus depending on the space, therefore I use the superscript s for the output and price index. In the empirical analysis - as in the single product case - I replace the output by the weighted average of deflated segment revenues.

As mentioned above, the working assumption throughout this paper is that only the relevant variables at the firm level are observed, which is an aggregation of the product-level variables. This is the case in most of the studies using firm-level data to estimate a production function. However, as I will discuss later on in detail, I have information on the product market linked to the firm-level data which allows me to put somewhat more structure on the way the product-level demand and production are aggregated.

Proceeding as in the single product case, the revenue of product j of firm i is $r_{ijt} = p_{ijt} + q_{ijt}$ and using the demand system as expressed in equation (8) I get the following expression for the product-firm revenue r_{ijt}

$$r_{ijt} - p_{st} = \left(\frac{\eta_s + 1}{\eta_s}\right) x_{ijt}\alpha - \frac{1}{\eta_s}q_{Ist} + \left(\frac{\eta_s + 1}{\eta_s}\right)(\omega_{ijt} + u_{ijt}^q) - \frac{1}{\eta_s}\xi_{ijt} - \frac{1}{\eta_s}u_{ijt}^d \qquad (9)$$

I have assumed that the production function q_{ij} for every firm i for all its products M_i is given by the same production function (1) and it implies that the production technology for every product is the same and that no cost synergies are allowed on the production side. In Appendix B I relax this assumption and show a reduced form approach to allow for some spillovers in the production process.

As before I substitute in the production technology as given by equation (1) where now a product subscript j is added. The aggregation from product to firm-level can be done in various ways and ultimately depends on the research question and the data at hand. If product specific inputs and revenues are available, the same procedure as in the single product firm applies, i.e. estimating a revenue production function by product j. However, observing revenue and output by product is hardly ever the case and so some assumptions have to be made in order to aggregate the product-level revenues to the firm level (the unit of observation in most empirical work). For notation purposes I assume a constant demand elasticity across products (η) and I aggregate the product-firm revenue to the firm revenue by taking the sum over the number of products produced M_{it}, i.e. $R_{it} = \sum_j^{M_i} R_{ijt}$ as in Melitz (2001). This leads to the following equation

$$\tilde{r}_{it} = \beta_0 + \beta_l l_{it} + \beta_m m_{it} + \beta_k k_{it} + \beta_\eta q_{It} + \beta_{np}np_{it} + \left(\frac{\eta + 1}{\eta}\right)\omega_{it} + \frac{1}{|\eta|}\xi_{it} + u_{it} \qquad (10)$$

When allowing for segment specific elasticities η_s the term capturing (observed) demand shifters will be more complicated (see section 5.2.1). Here I assumed that inputs per product are used in proportion to the number of products ($X_{ijt} = \frac{X_{it}}{M_{it}}$) which introduces an additional term $\beta_{np}np_{it}$ where $np_{it} = \ln(M_{it})$. The input proportionality is driven by the lack of product-specific input data such as the number of employees that are used for a given product j. As mentioned above, in Appendix B I relax the production aggregation from product to the firm level by essentially introducing a matrix that captures synergies from combining production of any 2 given segments within a single firm.

Productivity and demand shocks are assumed to occur at the firm level and u_{it} captures all the *i.i.d.* terms from both demand and supply (aggregated over products).[19] The demand shifter q_{Ist} is crucial as it allows me to identify the (segment specific) elasticity of demand through the assumption that it captures shocks in demand that are independent of the production function inputs and unobserved productivity. Furthermore it will turn out to be firm specific as I allow the demand elasticity to differ across products or segments of products. The latter is a result of allowing for firm specific product mixes and therefore each firm faces a (potential) different total demand over the various products it owns.

3 Estimation strategy and productivity estimates

I now briefly discuss how to estimate the demand and production function parameters. Secondly, I allow for investment to depend on the unobserved demand shocks (ξ) in the underlying Olley and Pakes (1996) model and I suggest a simple way (given the data I have) to control for this. Finally, I discuss the resulting productivity estimate and how it should be corrected for in the presence of product differentiation and multi-product firms. I also provide a discussion on the importance of miss-measured productivity (growth) using the standard identification methods.

3.1 Estimation strategy: single and multi-product firms

Estimating the regression in (7) is similar to the Olley and Pakes (1996) correction for simultaneity, only now an extra term has to be identified.[20] As in Melitz (2001) I group the two unobservables productivity ω_{it} and demand shock ξ_{it} into 'one unobservable' $\widetilde{\omega}_{it}$. Introducing the demand side clearly shows that any estimation of productivity also captures firm/product specific unobservables such as product quality for instance.

I assume that the unobserved demand and productivity component follow the same stochastic process, i.e. a first order Markov process with the same rate of persistence.[21] Productivity is assumed to follow an exogenous process and cannot be changed by investment or other firm-level decision variables such as R&D or export behavior (De Loecker, 2007).[22] Both the productivity shock ω_{it} and the demand shock ξ_{it} are known to the firm when it makes the decision on

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[19] Foster, Haltiwanger and Syverson (forthcoming) do not observe inputs at the plant level, they observe product specific revenues which allows them to proceed by assuming that inputs are used in proportion given by the share of a given product in total firm revenue.

[20] In the case of multi-product firms an additional parameter has to be identified. The identification depends on whether one allows the market structures to be different for single and multi-product firms.

[21] A possible extension to this is to assume that the quality and the productivity shock follow a different Markov process. Therefore one can no longer collapse both variables into one state variable (see Petropoulus 2000 for explicit modeling of this). For now I assume a scalar unobservable (productivity/quality) that follows a first order Markov process. However, I can allow for higher order Markov processes and relax the scalar unobservable assumption as suggested in Ackerberg and Pakes (2005), see later on.

[22] Muendler (2004) allows productivity to change endogenously and suggests a way to estimate it. Buettner (2004) introduces R&D and models the impact of this controlled process on unobserved productivity. Ackerberg and Pakes (2005) discuss more general extensions to the exogenous Markov assumption of the unobserved productivity shock.

the optimal level of inputs (labor and material inputs). The new unobserved state variable in the Olley and Pakes (1996) framework is now $\widetilde{\omega}_{it} = (\omega_{it} + \xi_{it})$ and this is equivalent to Melitz's (2001) representation. Technically, the equilibrium investment function still has to be a monotonic function with respect to the productivity shock, $\widetilde{\omega}_{it}$, in order to allow for the inversion as in Olley and Pakes (1996)

$$i_t = i_t(k_t, \widetilde{\omega}_t) \Leftrightarrow \widetilde{\omega}_t = h_t(k_t, i_t) \tag{11}$$

Here I have been more explicit on the nature of the unobservable $\widetilde{\omega}_{it}$ containing both unobserved demand (quality) and productivity. However, it does not change the impact on investment. A firm draws a shock consisting of both productivity and demand shocks and the exact source of the shock is not important as a firm is indifferent between selling more given its inputs due to an increased productivity or say the increased 'quality perception' of its product(s). We could even interpret investment in a broader sense, both as investment in capital stock and advertising. I replace the productivity $\widetilde{\omega}_{it}$ component by a polynomial in capital and investment, recovering the estimate on capital in a second stage using non linear least squares. The demand parameters, labor and material are all estimated in a first stage under the identifying assumption that the function in capital and investment proxies for the unobserved product/quality shock.[23]

$$\widetilde{r}_{it} = \beta_0 + \beta_l l_{it} + \beta_m m_{it} + \beta_\eta q_{It} + \phi_t(k_{it}, i_{it}) + u_{it} \tag{12}$$

A key parameter that I identify in this first stage is the estimate of the markup (β_η) which is identified by independent variation in demand shocks either at the industry (q_{It}) or segment level (q_{Ist}) depending on the specification I consider.

Note that the $\phi_t(.)$ is a solution to a complicated dynamic programming problem and depends on all the primitives of the model like demand functions, the specification of sunk costs, form of conduct in the industry and others (Ackerberg, Benkard, Berry and Pakes, 2005). My methodology brings one of these primitives - demand - explicitly into the analysis and essentially adds explicitly information to the problem by introducing demand variables in the first stage. Remember that this is required in order to recover estimates for true productivity (ω_{it}) when firm-level prices are not observed.

The identification of the capital coefficient in a second stage will now improve as the estimate for ϕ_{it} is now purified from demand shocks due to the introduction of demand variables in the first stage. This is important as ϕ_{it} is crucial to identify to the capital coefficient. In a second stage (13) the variation in the variable inputs and the demand variation is subtracted from the deflated revenue to identify the capital coefficient. As in Olley and Pakes (1996) the news component in the productivity/quality process is assumed to be uncorrelated with capital in the same period since capital is predetermined by investments in the previous year.

$$\widetilde{r}_{it+1} - b_l l_{it+1} - b_m m_{it+1} - b_\eta q_{It+1} = c + \beta_k k_{it+1} + g(\widehat{\phi}_{it} - \beta_k k_{it}) + e_{it+1} \tag{13}$$

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[23]Dynamic panel data econometrics uses lag structure and IV techniques to identify the production function parameters (Arellano and Bond, 1991).

where b is the estimate for β out of the first stage. Note that here I need to assume that unobserved demand and productivity shock follow the exact same Markov process in order to identify the capital coefficient. If the demand shock does not follow the same process and depends on productivity identification is only possible through an explicit demand estimation as e.g. Berry, Levinsohn and Pakes (1995) in order to produce an estimate for ξ_{it}. Another way out is to assume that the unobserved demand shock is uncorrelated with capital and has no lag structure, but that would leave us back in the case where it is essentially ignored when estimating a revenue generating production function.

The correction for the sample selection problem due to the non random exit of firms is as in the standard framework and leads to adding the predicted survival probability P_{it+1} in $g(.)$ in equation (13). The predicted probability is obtained from regressing a survival dummy on a polynomial in capital and investment.

Productivity $(\widehat{\omega}_{it})$ is then recovered by plugging in the estimated coefficients in the production function, $(\widetilde{r}_{it} - b_l l_{it} - b_m\, m_{it} - b_k k_{it} - b_\eta q_{It}) \frac{\widehat{\eta}}{\widehat{\eta}+1} = \widehat{\omega}_{it}$.

The suggested framework does not rule out alternative proxies for the unobserved productivity shock. Levinsohn and Petrin (2003) use intermediate inputs as a proxy.[24] Recently there has been some discussion of the validity of both proxy estimators. The first stage of the estimation algorithm potentially suffers from multicollinearity and the investment or material input function might not take out all the variation correlated with the inputs (Ackerberg, Caves and Frazer 2004). The criticism essentially comes from the assumptions of the underlying timing of the input decisions on labor and materials or investment. If indeed the first stage would suffer from multicollinearity, one can no longer invert the productivity shock and the estimates would not be estimated precisely. However, it is clear from the Ackerberg et al. (2004) that the my procedure does not suffer from this critique under the following timing assumptions: labor is chosen without perfect knowledge of the productivity shock. As noted by Olley and Pakes (1996), one can test whether the non parametric function used in the first stage is well specified and is not collinear with labor by introducing the labor coefficient in the last stage when identifying the capital coefficient.[25]

3.2   Unobserved demand shocks and productivity

So far I have assumed that the unobservable $\widetilde{\omega}_{it}$ - including both unobserved productivity and unobserved demand shocks (such as quality) - can be substituted by a non parametric function in investment and capital. The underlying assumption in that case is that investment proxies both the shocks in productivity (ω_{it}) and unobserved demand shocks (ξ_{it}). I now relax this by allowing investment to explicitly depend on another unobservable - a demand shock - that

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[24]The choice among the different proxy estimators depends on many things such as the share of firms having non zero investments, and the assumptions one is willing to make. (Appendix C).

[25]Also see De Loecker (2007) where this test is implemented and the labor coefficient is found to be insignificant throughout all specifications when running $\widetilde{r}^*_{it+1} = c + \beta_k k_{it+1} + g(\widehat{\phi}_t - \beta_k k_{it}) + \beta_c l_{it} + e_{it+1}$.

varies across firms as suggested in Ackerberg and Pakes (2005). This notion also follows from the discussion throughout the paper that both demand and production related shocks have an impact on observed revenue. Note that unobserved demand shocks would not enter the production function if we would observe physical output or firm-level prices when the investment policy function does not depend on say quality. However, when investment is allowed to depend on an unobserved demand shock (quality) as well, it enters through the productivity shock even when physical output or firm-level prices are observed.

In this section we have a demand shock entering both through the investment policy function and through the use of revenue to proxy for output at the firm level. The details of the estimation thus depend on whether the demand shock (quality) enters both into the demand system *and* the investment function. In the empirical application I will estimate both versions using firm-product dummies to control for unobserved product specific demand shocks. This will control for the cross sectional variation in product specific demand shocks. However, time variant demand shocks are not picked up. For instance, if we would interpret ξ_{it} to capture quality only it would imply that quality improvements are not controlled for and hence still end up in the productivity estimates. I refer to Appendix A.3 for a more detailed discussion on this. I show that if a control variable s_{it} (e.g. product dummies) for ξ_{it} exists that the first stage of the estimation algorithm looks as follows.

$$\widetilde{r}_{it} = \beta_0 + \beta_l l_{it} + \beta_m m_{it} + \beta_\eta q_{It} + \widetilde{\phi}_t(k_{it}, i_{it}, s_{it}) + u_{it} \tag{14}$$

In the case where the investment policy function does not depend on unobserved demand shocks, the control variable s_{it} enters just as an additional demand variable (see section 5.2.2). The use of these extra (product specific) demand side controls are potentially important in obtaining consistent estimates for the markup(s). In the context of a trade liberalization process the error term u_{it} will still capture demand shocks due to changes in quota protection. Those changes in protection are potentially correlated with the aggregate (segment) demand shifters Q_{It} (Q_{Ist}) and might lead to biased estimates of η (η_s). I will come back to this point in section 6 where I introduce the product-specific quota variables and how they impact firm-level demand.

3.3 Inference using standard measured productivity

When comparing with the standard approach to recover an estimate for productivity, it is clear that when estimating equation

$$\widetilde{r}_{it} = \beta_0 + \beta_l l_{it} + \beta_m \, m_{it} + \beta_k k_{it} + \omega_{it}^m + u_{it} \tag{15}$$

where I denote ω_{it}^m as *measured productivity*, that the resulting productivity estimate (residual) is miss-measured. It captures demand shocks and product mix variation on top of the potentially differently estimated coefficients β_l, β_m, β_k and β_0. For now I assume away the unobserved demand shock ξ_{it} and focus on the unobserved productivity shock. The resulting measured

productivity ω_{it}^m relates to the true unobserved productivity ω_{it} in the following way

$$\omega_{it} = (\omega_{it}^m - \beta_\eta q_{It} - \beta_{np} np_{it}) \left(\frac{\eta}{\eta + 1} \right) \tag{16}$$

The estimated productivity shock consistent with the product differentiated demand system and multi-product firms is obtained by substituting in the estimates for the true values (β_η, β_{np} and η). This shows that any estimation of productivity - including the recent literature correcting for the simultaneity bias (Olley and Pakes 1996 and Levinsohn and Petrin 2003) is biased in the presence of imperfect output markets and multi-product firms. Assuming an underlying product market a simple correction is suggested, i.e. subtract the demand variation and the number of products and correct for the degree of product differentiation. One can even get the demand parameter out of a separate (and potentially more realistic) demand regression. Note that in the case of single product firms operating in a perfectly competitive market the estimated productivity corresponds to the true unobservable, given that the simultaneity and selection bias are addressed as well.

It is clear from equation (16) that the degree of product differentiation (measured by η) only re-scales the productivity estimate. However, when the demand parameter is allowed to vary across product segments, the impact on productivity is not unambiguous. The number of products per firm M_i does change the cross sectional (across firms) variation in productivity and changes the ranking of firms and consequently the impact of changes in the operating environment or firm-level variables on productivity.

In a more general framework of time varying number of products per firm (M_{it}) the bias in measured productivity ω_{it}^m is given by (17). The traditional measure ω_{it}^m captures various effects in addition to the actual productivity shock ω_{it}.

$$\omega_{it}^m = \beta_{\eta_t} q_{It} + \beta_{np_t} np_{it} + \left(\frac{\eta + 1}{\eta} \right) \omega_{it} + \frac{1}{|\eta|} \xi_{it} \tag{17}$$

This expression sheds somewhat more light on the discussion whether various competition and trade policies have had an impact on productive efficiency. There is an extensive literature using a two stage approach where productivity is estimated in a first stage and then regressed on a variable of interest. However, in the first stage the relation of that variable of interest with demand related variance is omitted. Pavcnik (2002) showed that tariff liberalization in Chile was associated with higher productivity, where essentially an interaction of time dummies and firm trade orientation was used to identify the trade liberalization effect on productivity.[26] In terms of my framework, this measure of opening up to trade might also capture changes in prices and in the product mix of firms. Increased *measured productivity* is clearly more than pure productivity gains. It can be driven by any of the components in expression (17). It is exactly the fact that changes in the operating environment are potentially correlated with some or all of these components that makes inference using *standard productivity measures* (ω_{it}^m) problematic.

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[26] I refer to this paper among a large body of empirical work as the analysis of productivity is done by controlling for the simultaneity bias and the selection bias as in Olley and Pakes (1996).

Measuring increased productivity without taking into account the demand side of the output market and the degree of multi-product firms might thus have nothing to do with an *actual productivity* increase.[27] Even in the case of single product firms measured productivity growth ($\Delta\omega_{it}^m$) captures demand shocks and changes in prices. These biased productivity (growth) measures are then regressed upon variables potentially capturing both cost and demand shifters making any conclusion drawn out of these set of regressions doubtful.

It is straightforward to show the various biases one induces by using miss-measured productivity in a regression framework. Consider the following regression equation where the interest lies in δ_1 verifying the impact of d_{it} on measured productivity

$$\omega_{it}^m = \delta_0 + \delta_1 d_{it} + z_{it}\lambda + \varepsilon_{it} \tag{18}$$

where z_{it} captures a vector of control variables and ε_{it} is an *i.i.d.* error term. Using expression (17) it is straightforward to verify the different sources of correlation that bias the estimate for δ_1

$$\frac{\partial E(\omega_{it}^m)}{\partial d_{it}} = \frac{\partial E((q_{It} + \xi_{it})/|\eta|)}{\partial d_{it}} + \frac{\partial E(np_{it})}{\partial d_{it}} + \frac{\partial E((\eta + 1)/\eta)\omega_{it}}{\partial d_{it}} \tag{19}$$

where the expectation is conditional upon z_{it}. It is clear that impact of d_{it} on productivity (ω_{it}) is biased and the specific question and data at hand should help to sign the bias introduced by the various sources. For instance, if d_{it} captures some form of trade liberalization (or protection), it is expected to have an impact on the industry's total output and elasticity of demand and results in a biased estimate for coefficient δ_1.

In addition to the various other correlations leading to a biased estimate, the point estimate of the productivity effect is multiplied by the inverse of the (firm specific) markup. Konings and Vandenbussche (2005) showed that markups increased significantly during a period of trade protection after antidumping filings in various industries. The second term in (19) captures the correlation between the product mix and d_{it}. Bernard, Redding and Schott (2003) suggest that an important margin along which firms may adjust to increased globalization and other changes in the competitive structure of markets is through changing their product mix. I will empirically verify the importance of this bias when evaluating the impact of decreased quota protection in the Belgian textile industry on estimated productivity in section 5.

4   The Belgian textile industry: Data and institutional details

I now turn to the dataset that I use to apply the methodology suggested above and in a later stage to analyze the trade liberalization process measured by a significant drop in quota protection. My data covers firms active in the Belgian textile industry during the period 1994-2002. The firm-level data are made available by the National Bank of Belgium and the database is

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[27]Harrison (1994) builds on the Hall (1988) methodology to verify the impact of trade reform on productivity and concludes that "... *ignoring the impact of trade liberalization on competition leads to biased estimates in the relationship between trade reform and productivity growth*".

commercialized by BvD BELFIRST. The data contains the entire balance sheet of all Belgian firms that have to report to the tax authorities. In addition to traditional variables - such as revenue, value added, employment, various capital stock measures, investments, material inputs - the dataset also provides detailed information on firm entry and exit behavior.

FEBELTEX - the employer's organization of the Belgian textile industry - reports very detailed product-level information on-line (www.febeltex.be). More precisely, they list Belgian firms (311) that produce a certain type of textile product. The textile industry can be characterized by 5 different subsectors: i) interior textiles, ii) clothing textiles, iii) technical textiles, iv) textile finishing and v) spinning. Within each of these subsectors products are listed together with the name of the firm that produces it. This allows me to construct product-level information for each firm including the location of those products in the different segments of the textile industry. In Table A.1 I list the segments and the various product categories.

I match the firms listing product information with the production dataset (BELFIRST) and I end up with 308 firms for which I observe both firm-level and product-level information.[28] The average size of the firms in the matched dataset is somewhat higher than the full sample, since mostly bigger firms report the product-level data. Even though I loose some firms due to the matching of the product and the production datasets, I still cover 70 percent (for the year 2002) of total employment in the textile industry.[29]

By adding the rich source of product-level data, it is clear that the industrial classification codes (NACE BELCODE) are sometimes incomplete as they do not necessarily map into markets. If one would merely look at firms producing in the NACE BELCODE 17, there would be some important segments of the industry left out, e.g. the subsector technical textiles also incorporates firms that produce machinery for textile production and these are not always in the NACE BELCODE 17 listings. It is therefore important to take these other segments into the analysis in order to get a complete picture of the industry.

Before I turn to the estimation I report some summary statistics of both the firm-level and product-level data. In Table 1 summary statistics of the variables used in the analysis are given. The average firm size is increasing over time (11 percent). In the last column the producer price index (PPI) is presented. It is interesting to note that since 1996 producer prices fell, only to recover in 2000. Sales have increased over the sample period, with a drop in 1999. However, measured in real terms this drop in total sales was even more sharp. Furthermore I

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[28] After matching the two sources of data it turns out that a very small fraction - 17 - of firms included in the FEBELTEX listing are also active in wholesale of specific textiles. I ran all specifications excluding those firms since they potentially do not actually produce textile and all results are invariant to this.

[29] A downside is that the product-level information (number of products produced, segments and which products) is time invariant and leaves me with a panel of firms active until the end of my sample period. Therefore I check whether my results are sensitive to this by considering a full unbalanced dataset where I control for the selection bias (exit before 2000) as well as suggested in Olley and Pakes (1996). I can do this as the BELFIRST dataset provides me with the entire population of textile producers. The results turn out to be very similar as expected since the correction for the omitted price variable is essentially done in the first stage of the estimation algorithm. The variation left in capital is not likely to be correlated with the demand variables and therefore I only find slightly different estimates on the capital coefficient.

also constructed unit prices at a more disaggregated level (3 digit NACEBELCODE) by dividing the production in value by the quantities produced and the drop in prices over the sample period is even more prevalent in specific subcategories of the textile industry and quite different across different subsectors (see Appendix A.).

Together with the average price decrease, the industry as whole experienced a downward trend in sales at the end of the nineties. The organization of employers, FEBELTEX, suggests two main reasons for the downward trend in sales. A first reason is a mere decrease in production volume, but secondly the downward pressure on prices due to increased competition has played a very important role. This increased competition stems from both overcapacity in existing segments and from a higher import pressure from low wage countries, Turkey and China more specifically.[30] Export still plays an important role, accounting for more than 70% of the total industry's sales in 2002. A very large fraction of the exports are shipped to other EU member states and this is important as the quota restrictions are relevant at the EU level. The composition of exports has changed somewhat, export towards the EU-15 member states fell back mainly due to the strong position of the euro with respect to the British Pound and the increased competition from low wage countries. This trend has been almost completely offset by the increased export towards Central and Eastern Europe. The increased exports are not only due to an increased demand for textile in these countries, but also due to the lack of local production in the CEECs.

For each firm in the dataset I observe product-level information. For each firm I know the number of products produced, which products and in which segment(s) the firm is active. There are five segments: 1) Interior, 2) Clothing, 3) Technical Textiles, 4) Finishing and 5) Spinning and Preparing (see Appendix A. for more on the data). In total there are 563 different products, with 2,990 product-firm observations. On average a firm has about 9 products and 50 percent of the firms have 3 or fewer products. Furthermore, 75 percent of the firms are active in one single segment. This information is in itself unique and ties up with a recent series of papers by Bernard et al. (2003) looking at the importance of differences in product mix across firms where a 5 digit industry code is the definition of a product. Given I use a less aggregated definition of a *product*, it is not surprising that I find a higher average number of products per firm.

Table 2 presents a matrix where each cell denotes the percentage of firms that is active in both segments. For instance, 4.8 percent of the firms are active in both the Interior and Clothing segment. The high percentages in the head diagonal reflect that most firms specialize in one segment, however firms active in the Technical and Finishing segment tend to be less specialized as they capture applying and supplying segments, respectively. The last row in Table 2 gives the number of firms active in each segment. Again since firms are active in several segments, these numbers do not sum up to the number of firms in my sample.

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[30] An example is the filing of three anti-dumping and anti-subsidy cases against sheets import from India and Pakistan. Legal actions were also undertaken against illegal copying of products by Chinese producers (Annual Report of FEBELTEX; 2002). In section 6 I analyze the productivity dynamics during this increased competition period.

The same exercise can be done based on the number of products and as shown in Table 3 the concentration into one segment is even more pronounced. The number in each cell denotes the average (across firms) share of a firm's products in a given segment in its total number of products. The table above has to interpreted in the following way: firms that are active in the Interior segment have (on average) 83.72 percent of all their products in the Interior segment. The analysis based on the product information reveals even more that firms concentrate their activity in one segment. However, it is also the case that firms that are active in the Spinning segment (on average) also have 27.2 percent of their products in the Technical textile segment. Firms active in any of the segments tend to have quite a large fraction of their products in Technical textiles, 8.27 to 27.7 percent. Finally the last two rows of Table 3 show the median and minimum number of products owned by a firm across the different segments. Firms producing only 2 (or less) products are present in all five segments, but the median varies somewhat across segments (see Appendix A.1 for a more detailed description of the segments). It is this additional source of demand variation that I will use to construct segment demand shifters to estimate segment markups. This is in contrast to Melitz and Levinsohn (2002) who do not observe any product-level data and have to rely on the number of firms active in the industry to estimate one markup for the industry.

5 Estimated production and demand parameters

In this section I show how the estimated coefficients of a revenue production function are reduced form parameters and that consequently the actual production function coefficients and the resulting returns to scale parameter are underestimated. Furthermore, I introduce two additional sources of demand variation at the product and segment level to control for unobserved firm-level prices The two sources - segment demand shifters and product dummies - allow for different product-level demand intercepts and different slopes for the various segments of the industry. A direct implication is that each firm will face different demand conditions as they differ in their product mix both within and across segments.

5.1 The estimated coefficients of augmented production function

I compare my results with a few base line specifications: [1] a simple OLS estimation of equation (2), the Klette and Griliches (1996) specification in levels [2] and differences [3], $KG\ Level$ and $KG\ Diff$ respectively. Furthermore I compare my results with the Olley and Pakes (1996) estimation technique to correct for the simultaneity bias in specification [4]. In specification [5] I proxy the unobserved productivity shock by a polynomial in investment and capital and the omitted price variable is controlled for as suggested by Klette and Griliches (1996). Note that here I do not consider multi-product firms, I allow for this later when I assume segment specific demand elasticities.

I replace the industry output Q_{It} by a weighted average of the deflated revenues, i.e. $Q_{It} =$

$(\sum_i ms_{it} R_{it}/P_{It})$ where the weights are the market shares. This comes from the observation that a price index is essentially a weighted average of firm-level prices where weights are market shares (see Appendix A.2).

Table 4 shows the results for these various specifications. Going from specification [1] to [2] it is clear that the OLS produces reduced form parameters from a demand and a supply structure. As expected, the omitted price variable biases the estimates on the inputs downwards and hence underestimates the scale elasticity. Specification [3] takes care of unobserved heterogeneity by taking first differences of the production function as in the original Klette and Griliches (1996) paper and the coefficient on capital goes to zero as expected (see section 1). In specification [4] we see the impact on the estimates of correcting for the simultaneity bias, i.e. the labor coefficient is somewhat lower and the capital coefficient is estimated higher as expected. The omitted price variable bias is not addressed in the Olley and Pakes (1996) framework as they are only interested in a sales per input productivity measure. Both biases are addressed in specification [5] and the effect on the estimated coefficients is clear. The correction for the simultaneity and omitted price variable go in opposite direction and therefore making it hard to sign the total bias a priori.

The estimate on the capital coefficient does not change much when introducing the demand shifter as expected since the capital stock at t is predetermined by investments at $t-1$, however, it is considerably higher than in the Klette and Griliches (1996) approach. The correct estimate of the scale elasticity $(\alpha_l + \alpha_m + \alpha_k)$ is of most concern in the latter and indeed when correcting for the demand variation, the estimated scale elasticity goes from 0.9477 in the OLS specification to 1.1709 in the KG specification. The latter specification does not take control for the simultaneity bias which results in upward bias estimates on the freely chosen variables labor and material. This is exactly what I find in specification [5], i.e. the implied coefficients on labor drops when correcting for the simultaneity bias (labor from 0.3338 to 0.3075).[31]

The estimated coefficient on the industry output variable is highly significant in all specifications and is a direct estimate of the Lerner index. I also show the implied elasticity of demand and markup. Moving across the various specifications, the estimate of the average Lerner index (or the markup) increases as I control for unobserved firm productivity shocks. Moving from specification [2] to [3] I implicitly assume a time invariant productivity shock which results in a higher estimated Lerner index (from 0.2185 to 0.2658). In specification [5] productivity is modelled as a Markov process and no longer assumed to be fixed over time. Controlling for the unobserved productivity shock leads to a higher estimate of the Lerner index (around 0.30) as the industry output variable no longer picks up productivity shocks common to all firms as

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[31]Note that here my panel is only restricted to having firms with observations up to the year 2002 in order to use the product-level information and thus allows for entry within the sample period. However, as mentioned before my estimates of the production function are robust to including the full sample of firms. To verify this, I estimate a simple OLS production function on an unbalanced dataset capturing the entire textile sector. The capital coefficient obtained in this way is 0.0956 and is very close to my estimate in the matched panel (0.0879), suggesting that the sample of matched firms is not a particular set of firms.

picked up by investment and capital.

Finally, an interesting by-product of correcting for the omitted price variable is that I recover an estimate for the elasticity of demand and for the markup. The implied demand elasticities are around -3 and the estimated markup is around 1.4.[32] These implied estimates are worth discussing for several reasons. First of all, this provides us with a a check on the economic relevance of the demand model I assumed. Secondly, the implicit working assumption in most empirical work is that $\eta = -\infty$ and the estimates here provide a direct test of this. Thirdly, they can be compared to other methods (Hall 1988 and Roeger 1995) that estimate markups from firm-level production data.

The message to take out of this table is that both the omitted price variable and the simultaneity bias are important to correct for, although that the latter bias is somewhat smaller in my sample. It is clear that this will have an impact on estimated productivity. The estimated reduced form parameters (β) do not change much when controlling for the omitted price variable in addition to the simultaneity bias correction since the control is (in these specifications) not firm specific. However, it has a big impact on the estimated production function parameters (α), which by itself is important if one is interested in obtaining the correct marginal product of labor for instance. The industry output variable captures variation over time of total deflated revenue and as Klette and Griliches (1996) mention therefore potentially picks up industry productivity growth and changes in factor utilization. If all firms had a shift upwards in their production frontier, the industry output would pick up this effect and attribute it to a shift in demand and lead to an overestimation of the scale elasticity. In my approach, the correction for the unobserved productivity shock should take care of the unobserved industry productivity growth if there is a common component in the firm specific productivity shocks (ω_t).

In the next section I introduce product-level information that allows for firm specific demand shifters as firms have different product portfolios over the various segments of the industry. Estimated productivity will be different due to different estimated parameters (β) and additional demand controls capturing the shifts in demand for the products of a firm in a given segment of the industry. The estimated coefficients on the inputs (β) will potentially change as I further control for unobserved prices and the correlation of inputs with the output price through the introduction of additional rich demand side variation. The implied production function parameters (α) are expected to change as well due to a potentially different reduced form parameter β and different markup estimates for the various segments.

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[32] Konings, Van Cayseele and Warzynski (2001) use the Hall (1988) method and find a Lerner index of 0.26 for the Belgian textile industry, which is well within in the range of my estimates (around 0.30). They have to rely on valid instruments to control the for the unobserved productivity shock. A potential solution to overcome this is a method proposed by Roeger (1995) were essentially the dual problem of Hall (1988) is considered to overcome the problem of the unobserved productivity shock, however one is no longer able to recover an estimate for productivity.

5.2 Segment specific demand, unobserved product characteristics and pricing strategy

So far, I have assumed that the demand of all the products (and firms) in the textile industry face the same demand elasticity η and I have assumed that the demand shock u_{ijt}^d was a pure *i.i.d.* shock. Before I turn to the productivity estimates, I allow for this elasticity to vary across segments and I introduce product dummies. In Appendix A.2 I present the evolution of producer prices in the various subsectors of the textile industry and it is clear that the price evolution is quite different across the subsectors suggesting that demand conditions were very different across subsectors and from now on I consider the demand at the 'segment' level.

Firstly, I construct a segment specific demand shifter - segment output deflated - and discuss the resulting demand parameters. Secondly, I introduce product dummies to control for product specific shocks, essentially controlling for ξ_j. Finally, I split up my sample according to firms being active in only 1 or more segments. Firms producing in several segments can be expected to have a different pricing strategy since they have to take into account whether their products are complements or substitutes. Note that here the level of analysis is that of a segment, whereas the pricing strategy is made at the individual product level.

5.2.1 Segment specific demand parameters

In this section I will show how introducing data on the (firm-specific) number of products produced and the location of products in the various segments, enables us to estimate segment specific markups. The latter is important as it allows us to control for markup differences across firms with different product portfolios. To see this, just take the situation where we estimate one markup for the industry and then apply the correction to obtain true productivity. If markups do differ across segments, productivity differences across firms will still capture differences in markups. This correction is important when we want to relate the productivity dynamics to changes in trade protection, especially since the latter varies quite significantly across products and thus segments.

The number of products produced by a firm M_i allows us to create segment specific demand shifters which are consistent with the demand system introduced in the previous section. Just as before we now allow for segment specific demand shifters Q_{Ist} and by definition are given by

$$Q_{Ist} = \frac{\sum_{i=1}^{N_s} ms_{ist} R_{ist}}{P_{Ist}} \tag{20}$$

where N_s is the number of firms in segment s, ms_{ist} is the market share of firm i in segment s, R_{ist} is the revenue of firm i in segment s and P_{Ist} is the average price in segment s. The two terms ms_{ist} and R_{ist} on the right hand side are typically not observed. Using M_i we can construct segment specific demand shifters that uses product mix variation across firms and I

use M_i to compute

$$R_{ist} = R_{it}\frac{M_{is}}{M_i} \tag{21}$$

$$ms_{ist} = \frac{R_{ist}}{\sum_i R_{ist}} \tag{22}$$

where M_{is} and M_i are the number of products firm i has in in segment s and in total, respectively. Now that we have segment output (Q_{Ist}) it suffices to weigh across segments according to $S_{is} = \frac{M_{is}}{M_i}$ to obtain a firm-specific total demand shifter. All firms now (potentially) face 5 different (segments) demand shifters and the product-mix variance in addition to the segment demand shifters are used to identify the segment markups β_{η_s}. The latter are - just like in the case of the single markup - the coefficients on the 5 terms $\ln(S_{is}Q_{Ist})$ in the augmented production function.[33]

In this way I weigh the various demand shifters by firm across segments according to how *important* a segment is for a firm's total revenue. This firm-specific importance is measured by the share of the number of products in a given segment. For example a firm with 9 out of its 10 products located in segment 1 will get a weight of 0.9 on demand shocks specific for segment 1. This additional source of variation across firms (using the firm-specific product mix) is then used to identify segment specific markups. It is clear that this approach might introduce some measurement error by forcing firm-segment revenues to be proportional to the share of the number of products sold in a given segment. However, as long as the proportionality is not violated in some systematic way across products and segments, it is not expected to bias my estimates in any specific way.

In this way the demand parameter is freed up to be segment-specific s by interacting the segment demand shifter (segment output) with the segment share variable S_{is}.[34] This implies that I will now recover markups for $s = \{1$ (*Interior*), 2 (*Clothing*), 3 (*Technical*), 4 (*Finishing*), 5 (*Spinning and Preparing*)$\}$. Note that the demand elasticity is now identified using firm specific variation as the share variable is firm specific and Tables 3 and 4 show the variation in the product mix of firms across segments.[35]

I now turn back to the general setup of the paper and denote $q_{ist} = \ln(S_{is}Q_{Ist})$ which captures the segment specific demand shifter weighted by the number of products a firm has in a given segment . The augmented production function I estimate is clearly extended by allowing

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[33]Note that here I have constrained the number of products per firm M_i to be time-invariant as in my dataset. Obviously when the product mix is observed at each point in time this introduces another rich source of identifying variation.

[34]I have also estimated demand parameters one level deeper, see Appendix A.1 for the structure of the segments. This leads to a model with 51 different demand elasticities and identification is somewhat harder as the number of observations for some of the products is insufficient. However, for a set of subsegments I recover significant and meaningful estimates for markups.

[35]As mentioned before, I do not observe the change of the product mix over time. It is reassuring, however, that based on the US Census data (Bernard et al. 2003) firms only add or drop about 1 product over a five year period, or less than 2 products over a nine year period which corresponds to my sample length (1994-2002). To the extend that this variation is not picked up by the proxy for ω_i, it potentially biases the input coefficients.

η to vary by segment s

$$\widetilde{r}_{it} = \beta_0 + \beta_l l_{it} + \beta_m m_{it} + \sum_{s=1}^{5} \beta_{\eta_s} q_{ist} + \beta_{np} np_{it} + \phi_t(i_{it}, k_{it}) + u_{it} \tag{23}$$

I present the estimated coefficients β_{η_s} and the distribution of the estimated demand parameter in Table 5. One can immediately read of the implied demand parameters for the various segments in the textile industry for those firms having all their products in one segment ($S_{it} = 1$).

Introducing multi-product firms in this framework explicitly implies a correction for the number of products produced. As mentioned before, since I do not observe the product specific inputs at the firm level, I have assumed that the product specific input levels are proportional to the total firm input, where the proportion is given by the number of products produced ($\ln M_i = np_i$). The coefficient on this extra term is negative and highly significant, however, it is hard to interpret especially in the context of the control function ($\omega_{it} = h(i_{it}, k_{it})$) as it is quite plausible that the investment decision of a firm depends on the number of products produced.

The first row in Table 5 shows the estimated coefficients implying significantly different demand parameters for the various segments. I also include the implied demand parameters relevant for firms having all their products in a given segment. For instance, firms having all their products in the segment Interior face a demand elasticity of -5.3. In panel B of table 5 I use the firm specific information on the relative concentration (S_{is}) and this results in a firm specific elasticity of demand and markup which are in fact weighted averages over the relevant segment parameters. I stress that this comes from the fact that firms have multiple products across different segments and therefore the relevant demand condition is different for every firm.[36]

5.2.2 Unobserved product characteristics

I now introduce product dummies to control for product specific unobserved demand shocks (ξ_j). Note that in my empirical implementation the unobserved demand shock - which is potentially correlated with the other demand variables (segment output) - is now time invariant and only product specific (ξ_j) due to the lack of time-varying product-mix information (as opposed to being firm and time specific in the theoretical setup).

In terms of section 3.2 the product dummies proxy for the unobserved demand shocks - that are product specific and potentially impacts the investment decision. I assume time invariant unobserved product characteristics and there are 563 products (K) in total (and a firm produces 9 of these on average) which serve as additional controls in the first stage regression (24). The product dummies are captured by $PROD_{ik}$ where $PROD_{ik}$ is a dummy variable being 1 if firm i has product k. The variation across firms in terms of their product mix allows me to identify the K product fixed effects and they have a specific economic interpretation.

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[36] The same is true for the estimated production function coefficients, since they are obtained by correcting for the degree of production differentiation which is firm specific (η_i).

Note that I introduce the product dummies motivating the need to correct for product specific demand shocks such as unobserved quality. However, they will also capture variation related to the production side and those two types of variations are not separable.[37] The identifying assumption for recovering an estimate on the capital coefficient is that productivity and the unobserved demand shock are independent. However, using the product dummies in the proxy for productivity, the identifying assumption becomes less strong, i.e. I filter out time invariant product unobservables. Note that in the standard approach for identifying the production coefficients, demand variation is not filtered out, both observed and unobserved. Here I allow for product unobservables and demand shocks to impact investment decisions, on top of proxying for the demand shocks by segment output and product dummies. Note that I assume that $\xi_{ijt} = \xi_j$ and I only control for product time invariant demand shocks as opposed to time varying firm-product specific demand shocks.

$$\widetilde{r}_{it} = \beta_0 + \beta_l l_{it} + \beta_m \, m_{it} + \sum_{s=1}^{5} \beta_{\eta s} q_{st} S_{is} + \beta_{np} np_i + \widetilde{\phi}_t \left(i_{it}, k_{it}, PROD_{i1}, ..., PROD_{iK} \right) + u_{it} \quad (24)$$

In Table 5 I show that the demand parameters do not change too much as expected, as well as the production related coefficients. However, the point estimates are more precise and 62 out of the 652 products are estimated significantly different from the reference product confirming the importance of controlling for time invariant product characteristics. As mentioned above the interpretation of these coefficients is somewhat harder as the product dummies are introduced to proxy for unobserved demand shocks, however, they will also pick up product-specific production related differences. As stressed before, all these extra controls come into play if the interest lies in getting an estimate on productivity taking out demand related variation.

In terms of economic interpretation, Table 5 suggests that firms operating in the Finishing segment (only) face less elastic demand. The high elastic demand segments are Interior and Spinning capturing products - like linen, yarns, wool and cotton - facing high competition from low wage countries.[38] In Appendix A.1 I relate these demand parameters to changes in output prices at more disaggregated level and I find that indeed in those sectors with relative high elastic demand, output prices have fallen considerably over the sample period.

5.2.3 Single versus multi-product firms

So far I have assumed that the pricing strategy of firms is the same whether it produces one or more products, or whether it is active in one or more segments. Remember that the revenue

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[37] I introduce the product dummies without interactions with the polynomial terms in investment and capital since that would blow up the number of estimated coefficients by K. This then coincides with assuming that the quality unobservable does not enter the investment policy function in the first stage and just correcting for the demand unobservable. However, it matters for the second stage, i.e. this variation is now *not* subtracted from deflated sales ($\widetilde{r}$) like the variable inputs. This would imply that the time invariant product dummies would proxy the unobserved demand shock completely. Therefore, the resulting productivity will still capture time variant demand shocks - say improved product quality.

[38] Increased international competition in the Interior and Spinning segments is documented in section 6 where quota protection is discussed.

observed at the firm-level is the sum over the different product revenues. Firms that have products in different segments are expected to set prices differently since they have to take into account the degree of complementarity between the different goods produced. I relax this by simply splitting my sample according to the number of segments a firm is active in. The underlying model of price setting and markups can be seen as a special case where own and cross elasticities of demand are restricted to be the same within a segment.

In the third row of Table 5 I present the estimated demand parameters for firms active in only 1 segment and for those active in at least 2. As expected the estimated demand elasticities for the entire sample are in between both. Firms producing products in different segments face a more elastic (total) demand since a price increase of one of their product also impacts the demand for their other products in other segments.[39] This is not the case for firms producing only in 1 segment, leading to lower estimated demand elasticities. It is clear that the modeling approach here does allow for various price setting strategies and different demand structures.

From the above it is clear that productivity estimates are biased in the presence of imperfect competitive markets and ignoring the underlying product space when considering firm-level variables. It is clear that the data at hand and the research question will dictate the importance of the various components captured by traditional productivity estimates. In the next section I analyze the productivity gains from the trade liberalization in the Belgian textile industry and I compare my results with the standard productivity estimates, which are in fact sales per input measures and not necessarily lead to the same conclusions.

6   Trade liberalization and productivity gains

In this section I introduce product-level quota restrictions as additional controls for the unobserved firm-level price variable in the demand system and consequently in the augmented production function. In section 5 I showed that the industry output and segment output variables were highly significant, however, they implied rather high markups and in turn relatively high returns to scale point estimates. Including the quota restriction variable is expected to lead to lower estimates on the demand shifters Q_{Ist} if anything as firms protected by quota are expected to have higher market share - if anything - and produce more. I will correct for the potential upward bias in the Lerner index. In addition the quota variable will control for additional variation in unobserved firm-level prices as producers are expected to be able to set higher prices if import is restricted even more so since quota tend to apply on suppliers with lower costs of production (wages). I model the quota restriction variable as an additional residual demand shock in the demand system and it will impact each firm demand intercept differently according to the firm's product mix.

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[39]Note that now the implied demand elasticities are given by the weighted sum over the various segments a firm is active in, where weights are the fraction of the number of products in a segment in the total number of products owned.

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First I introduce the quota data and discuss how it relates to the firm-level data. Secondly, I introduce the quota restriction measure into the augmented production function. The resulting estimated productivity is then used to verify to what extent that abolishing the quota on imports has contributed to *within-firm productivity gains* in the Belgian textile industry and how results using standard techniques to estimate productivity differ from the methodology suggested in this paper. In contrast to within-firm productivity changes, aggregate industry productivity can increase by the mere exit of lower productivity firms and/or the reallocation of market share towards more productive firms.[40] As shown in Syverson (2004), demand shocks might in turn impact the aggregate productivity distribution.

6.1 The quota data: raw patterns and a measure for trade liberalization

The quota data comes straight from the *SIGL database* constructed by the European Commission (2003) and is publicly available on-line (http://sigl.cec.eu.int/). Note that this data is at the EU level since Belgium has no national wide trade policy and so quota at the EU level are the relevant quota faced by Belgian producers. This database covers the period 1993-2003 and reports all products holding a quota. For each product the following data is available: the supplying country, product, year, quota level, working level, licensed quantity and quantity actually used by the supplying country.[41] From this I constructed a database listing product-country-year specific information on quota relevant for the EU market.

Before I turn to the construction of a variable capturing the quota restriction relevant at the firm level, I present the raw quota data as it shows the drastic changes that occurred in trade protection during my sample period 1994-2002. In addition to observing whether a given product is protected by a quota, the level of allowed import quantities measured in kilograms (kg) or number of pieces - depending on the product category - is provided. In total there are 182 product categories and 56 supplying countries, where at least one quota on a product from a supplier country in a given year applies. In terms of constructing a trade liberalization or protection measure various dimensions have to be considered.

Given the structure of the demand system and how the quota restriction will impact firm-level demand I create a composite variable that measures the extent to which a firm is protected (across its products). A first and most straightforward measure is a dummy variable that is 1 if a quota protection applies for a certain product category g on imports from country e in year t (qr_{egt}) and switches to zero when the quota no longer applies. However, increasing the quota levels is also consistent with opening up to trade and thus both dimensions are important to look at. Table 6 below shows the number of quota that apply for the sample period 1994-2002.

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[40]It is clear that decompositions of aggregate industry productivity using biased measures of firm-level productivity will provide different answers as to how important net entry, reallocation and within productivity growth are. In fact given the framework suggested here, it is easy to show how we over- (under) estimate the various components of aggregate productivity. Under the empirical relevant scenario that entrants charge lower prices, it is clear that the importance of entry is underestimated since $\omega_{it}^M = \omega_{it} + (p_{it} - p_{It})$.

[41]Appendix A.4 describes the quota data in more detail and provides two cases on how quota protection changed.

In addition I provide the average quota levels split up in kilograms and number of pieces, both expressed in millions.

It is clear from the second column that the number of quota restrictions have decreased dramatically over the sample period. By 2002 the number of quota fell by 54 percent over a nine year period and these numbers refer to the number of product-supplier restricted imports. Columns 3 to 6 present the evolution by unit of measurement and the same evolution emerges: the average quota level increased with 72 and 44 percent for products measured in kilograms and number of pieces, respectively. Both the enormous drop in the number of quota and the increase in the quota levels of existing quota, points to a period of significant trade liberalization in the EU textile industry. It is essentially this additional source of demand variation I will use to identify the demand parameters in the augmented production function and verify how this gradual opening up to foreign textile products has impacted firm-level productivity.

As mentioned above the product classifications in the quota data are different from the firm-level activity information and have to be aggregated to the firm-level revenue and input data. The average quota restriction (qr) that applies for a given product g is given by

$$qr_{gt} = \sum_e a_{et} qr_{egt} \tag{25}$$

where a_{et} is the weight of supplier e in period t. This measure is zero if no single quota applies to imports of product g from any of the supplying countries at a given time, and one if it holds for all supplying countries. A final step is to relate the quota restriction measure to the information of the firm revenue and production data. The 182 different quota product categories map into 390 different 8 digit product codes. The latter correspond to 23 (l) different 4 digit industry classifications (equivalent to the 5 digit SIC level in the US) allowing me to relate the quota restriction variable to the firm-level variables. Aggregating over the different product categories leaves me with a quota measure of a given 4 digit industry code. I consider the average across products within an industry l (qr_{it}) where a firm i is active in as given by (26).

$$qr_{it} = \frac{1}{N_{gt}} \sum_{g \in l(i)} qr_{gt} \tag{26}$$

In Figure 1 I show the evolution of the quota restriction variable given by (26) split up by segment. Again the same picture emerges, in all segments the average quota restriction has gone down considerably over the sample period, however, there are some differences across the various segments and it is this variation that will help to estimate the segment specific demand elasticities.

The construction of the quota restriction measures provides me with an additional control for the unobserved price variable and it is assumed to enter the demand system (4) as part of the residual demand shock in the demand system in addition to the pure $i.i.d.$ component u_{it}^d and unobserved demand shocks ξ_{it}. This implies that it is assumed to be independent (conditional on the other controls) of the input and investment choices.

6.2 Introducing quota restrictions in the demand system

I now introduce the average quota restriction qr_{it} in the demand system where I now have the following expression.

$$Q_{it} = Q_{It} \left(\frac{P_{it}}{P_{It}}\right)^{\eta} \exp(u_{it}^d + \xi_{it} + qr_{it}) \tag{27}$$

The interpretation of this model is to estimate the elasticity of substitution (demand) that is consistent with international competition. It implies that the intercept for each firm is allowed to differ according to the protection of its products.[42] I allow for segment specific demand elasticities and multi-product firms and I control for time invariant unobserved product effects using product dummies. This leads to the following augmented production function (28)

$$\begin{aligned}
\widetilde{r}_{it} &= \beta_0 + \beta_l l_{it} + \beta_m m_{it} + \sum_{s=1}^{5} \beta_{\eta_s} q_{ist} + \beta_{qr} qr_{it} + \beta_{np} np_i \\
&\quad + \phi_t(i_{it}, k_{it}) + \sum_{k=1}^{K} \lambda_k PROD_{ik} + u_{it}
\end{aligned} \tag{28}$$

where the term $\beta_{qr} qr_{it}$ captures the quota measures.[43] Before I present the estimated coefficients, I note that introducing the quota restriction information helps estimating the β_{η_s} and potentially the production function parameters. Table 7 presents the estimated Lerner indices (β_{η_s}) and compares them with the specification where the extra demand variation captured by the quota restriction is not included. I also recover product specific estimates and about 20 products are estimated significantly different from their respective segment average (see Appendix A.3). These can be interpreted as the product of segment specific Lerner indices and time invariant product shocks ξ_j under the assumption that the investment decision does not depend on the unobserved demand shock. This is the assumption implicitly made in expression (28) as they do no longer enter in the control function $\phi_t(i_{it}, k_{it})$.

The last 4 rows show the estimated production coefficients and the implied returns to scale. The estimate on the quota restriction variable immediately provides information on how standard estimated productivity estimates incorporate demand shifters.[44] We could immediately verify

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[42] I have also estimate a change in the slope of the demand curve (elasticity). The identification is somewhat harder as firms can be active in different segments experiencing different changes in the protection, however, the results are invariant.

[43] A well documented problem of using trade liberalization or protection measures in a regression framework is that they are potentially endogenous as firms might lobby for protection. In order to verify whether in my sample producers of certain product categories were able to keep higher level of protection, I ran a regression of qr_{ge2003} on qr_{ge1993} ($N = 1,097$) finding a strong negative relation which suggests that protection in *all* product categories decreased over time. In addition, when analyzing the productivity effects I include product category (l) dummies controlling for (time invariant) differences in lobbying-for-protection activities across producers active in different product categories.

[44] All the results are based on unweighted averages. I have also experimented using the quota levels to construct the weights. These would capture the importance of a given quota protection in the overall import restriction and the extent to which import demand for a given product can be substituted away to another supplier. Due to the different unit of measurement in the levels, the interpretation of a change in qr is less clear.

how the trade liberalization impacted productivity by decomposing the coefficient on the quota restriction variable qr_{it} into the (segment) markup and the productivity effect. However, we can only do this when the quota restriction does not impact the investment choices and if productivity is a simple linear function of qr_{it} only ($\omega_{it} = \theta_\omega qr_{it} + \widetilde{\omega}_{it}$). Given the structure of productivity and the demand system, we know that the coefficient on qr_{it} is given by $\left[\left(\frac{\eta+1}{\eta}\right)\theta_\omega + \frac{1}{|\eta|}\right]$. Using the range of estimates for η it is clear that the coefficient of -0.09 on qr_{it} implies a negative value for θ_ω as expected but rather big in magnitude (around 0.3). I will turn to the impact of the quota liberalization on productivity in the next section.

As expected, the coefficients on the segment output are estimated lower confirming the prior that the quota restriction measure is positively correlated with the segment output, i.e. higher protection, higher domestic production. As noted by Tybout (2000), the effect from restricting imports is that firms might exploit their enhanced market power and that protection is likely to increase the market size for domestic producers.

The estimates on the inputs are quite similar after introducing the additional demand information as expected, since these are just reduced form parameters. However the implied production coefficients do change since the estimated demand elasticities change and this is reflected in the lower estimated returns to scale. Note that the capital coefficient is estimated lower compared to Table 4 where no product-firm dummies were used. The latter capture time invariant product differences and improves the estimation of the capital coefficient by purifying the error term in the final stage (13) from any product-firm specific time invariant unobservables capturing quality differences on top of the observed demand variation across segments. This could also point to a positive correlation of capital intensity and output prices.

Finally, in Appendix A.3 I verify whether the estimates of the segment specific markups are sensitive to the underlying assumptions of the production process such as the timing of inputs with respect to the productivity shock and the substitution elasticity among inputs and I find that my estimated demand parameters are robust to this.

6.3   The impact of relaxing trade protection on productivity

The coefficient on the quota restriction variable is estimated highly significant and with a negative sign, -0.0886. As previous studies have shown productivity gains are associated with trade liberalization, although measured in different ways these studies essentially establish a highly significant positive correlation between productivity and opening up to trade.[45] The estimated productivity shock in a standard OP setup would then still include markups and demand shifts introduced by the change in trade policy. Therefore it is crucial to purify productivity estimates from the price and demand related variation in order to get at the true impact of trade liberalization on productivity and productivity growth. The distinction between both is important as to know whether opening up to trade does impact productivity growth and hence has a long

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[45] See Tybout (2000) for an overview and e.g. Pavcnik (2002) for a country study.

run impact on the efficiency of an economy.

The interpretation in my specification is somewhat more complicated. To the extent that the polynomial in capital and investment picks up the unobserved productivity shock, the quota restriction variable picks up demand shocks. However, it is clear that it will also pick up variation related to true productivity that is not controlled for by the polynomial in investment and capital. It is exactly the relation between productivity and the trade liberalization measure that is of interest.

In order to verify the extent to which trade liberalization - measured by a decrease in quota restrictions - has impacted the productivity of Belgian textile producers I follow the standard 2 stage approach and show how the results change when using my corrected productivity estimates. I consider the following regression

$$\widehat{\omega}_{it} = \delta_0 + \delta_1 qr_{it} + \delta_2 nqr_{it} + \varepsilon_{it} \tag{29}$$

where $\widehat{\omega}_{it}$ refers to the estimated productivity and I will consider various versions of (29). In all regressions I include quota product classification dummies (23 categories) capturing time invariant productivity (growth) differences among categories. Table 8 presents the estimates of δ_1 under various specifications.

Before I turn to each specification, it is clear that - across all specifications - using the standard OP productivity estimate leads to an overestimation of the impact of trade liberalization.[46] Note that a decrease in the quota restriction variable corresponds with less quota protection or opening up of trade. So a negative coefficient implies productivity gains from relaxing quota restrictions. In all specifications the sign is negative and highly significant and the interpretation of the coefficient is the productivity gain for abolishing quota on all products from all countries.

Specification I is the level regression and implies a 6.37 percent higher productivity for firms not protected by a single quota and using OP the estimate is much higher, 10.68 percent. Given the Markov assumption of productivity in the estimation algorithm and knowing that firm productivity estimates are highly persistent over time, specification II introduces lagged productivity as a regressor. The impact of the quota restriction variable is estimated more precise and somewhat lower. In specification III and IV, I run the regression in growth rates revealing the same pattern as in specification I. In specification IV, however, I include lagged levels of the quota restriction variable. Controlling for the lagged levels of the quota restriction measure leads to a higher point estimate on δ_1, showing that the impact of relaxing quota restrictions on productivity depends on the initial level of the quota. If the quota protection was initially low, there is not much impact on productivity. Specification V considers long differences (3 year period) and the results are robust to this, although estimated somewhat less precise due to the significant drop in observations.

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[46]Using the estimates one can derive that the segments with a relative high level of protection have higher markups as expected (e.g. Tybout 2000). This - together with the scaled point estimate - leads to a biased estimate of the effect of relaxing quota protection on standard estimated productivity (OP).

In order to recover an estimate of the elasticity of productivity with respect to quota restrictions, I evaluate this at the mean (of the change in quota restriction) by segment. Table 9 shows the impact of a 10 percent decrease in the quota restriction measure on productivity for the various segments and it further compares my results with those relying on the OP productivity estimates. A 10 percent decrease in the quota restriction measure can come about by products being no longer protected from all or some supplying countries.[47]

As established in the previous table trade liberalization leads to higher productivity, however, there are some differences across segments. A 10 percent decrease in my quota restriction measure leads only to a 1.6 percent higher productivity in the Finishing segment, as opposed to a 4.37 percent increase in the Interior segment. This result is what one would expect given the different paths of the quota restriction variable by segment as shown in Figure 1. The Finishing segment started out with a relatively low level of protection in 1994 (0.3) and stays rather flat after 1996. The other segments - with higher estimated elasticities - had much higher levels of protection initially, e.g. the Interior segment was highly protected ($qr = 0.85$) in 1994 and by 2002 protection was significantly lower ($qr = 0.3$). It is clear that the productivity gains are much smaller (more than halved) and this is what one would expect for firms operating in an advanced economy, as opposed to firms active in more developing regions. The results show that decomposing the residual from a sales generating production function into productivity and demand related factors, is important to evaluate the impact of trade liberalization on productivity.

Furthermore in Table 9, I present the elasticities evaluated at the mean of the change in the quota restriction for two different periods, 1994-1997 and 1998-2002. The first period is characterized by a sharper fall in the quota protection (see Table 9) and therefore leads to higher estimated elasticities. The sharp fall of the number of quota in the period 1994-1997 is consistent with the process of the preparation of EU enlargement towards Central and Eastern Europe (CEE). By the year 1998 almost all trade barriers between the EU and the candidate countries of CEE were abolished as part of the Europe Agreements (EC 2005). The Europe Agreements were setup to establish free trade in industrial products over a gradual, transition period. This implied that industrial products from the associated countries (mostly CEE) have had virtually free access to the EU since the beginning of 1995 with restrictions in only a few sectors, such as agriculture and textiles. However, even in the last period (1998-2002) the productivity gains are still estimated around 3 percent with the exception of the Finishing segment which had a relatively low level of quota protection throughout the sample period.

Finally, as mentioned before another channel through which the EU trade policy relaxed quota restrictions is by increasing the level of existing quota for a set of supplying countries. In order to verify the impact of this on productivity I consider only those industry categories (4 digit NACE) that have some form of protection, i.e. where I observe a positive level of

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[47]The average quota restriction measure is 0.43 and the average change in this measure is -0.05, which is around 10 percent.

protection and the unit of measurement of a quota level is constant within a given industry code (23 categories). This dimension of opening up to trade has been the predominant strategy for the EU when it comes to imports from outside CEE and other new EU member states and not as much through abolishing quota. In Table 10 I list the supplying countries where relaxing import restrictions mainly occurred through higher levels of quota. I report the increase in the average level per quota during my sample period 1994-2002. The countries listed have gained access to the EU textiles market under a significant increase of quota levels.

For instance the average quota level on textile products from Pakistan has more than doubled over a nine year period (129 and 144 percent depending on product category). This process is not captured by the quota restriction variable that picks up whenever a quota on a given product from a supplying country is abolished.

In order to verify the impact of increased quota levels - in addition to the abolishment of quota - I include a variable that measures the total level of quota (in logs) in a given industry in the regression framework of specification II. Specification VI in Table 10 shows the results of including the *level* variable. The quota restriction variable has a negative sign as before and the coefficient on the *level* variable is estimated with a positive sign: an increase in the level of quota is consistent with increased competition from foreign textiles products and has a positive effect on productivity. The point estimate is an elasticity and implies that if quota levels increase by 10 percent that productivity increases with 1.9 percent.

The simultaneous abolishment of quota protection and the increase in the quota levels are associated with higher productivity of Belgian textile producers. Productivity gains were higher for firms active in segments which initially were highly protected as they had to restructure more in order to face the increased competition from non-EU textile producers. However, the magnitude of the productivity gains are fairly small compared to those obtained with standard techniques. As mentioned before, the results presented in Table 10 can be interpreted as a decomposition of *measured productivity gains* from relaxing trade protection into true productivity gains and demand shocks. Here, I find that around 50 percent is only picking up actual productivity gains.

My results suggest that the channel through which trade liberalization impacts productivity is mostly by cutting off the inefficient producers from the productivity distribution and therefore increases the average productivity of the industry. However, the (within-firm) productivity gains for those producers that remain active are small and sometimes even negligible. These two observations then imply a very different interpretation of how opening up trade impacts individual firms. Furthermore, the reallocation of activities across surviving firms is not as closely tied to productivity, but rather an interplay of the ability to markup over costs and productivity.

7 Conclusion

In this paper I suggest a method to correct for the omitted price variable in the estimation of productivity. I have introduced a simple demand side and I explicitly allow firms to have multiple products. I introduce a simple aggregation from product space into firm space and derive a straightforward estimation strategy. I show that measured productivity increases need not to reflect actual productivity increase. This casts some doubt on the recent empirical findings that link changes in the operating environment - such as trade protection - on firm-level productivity (growth) in a two-stage approach. I illustrate this methodology by analyzing productivity in the Belgian textile industry using an unique dataset that in addition to firm-level data has product-level information. Adding extra product-level information to the plant-level data appears to be a successful first step in separating out demand variation and product mix from estimated productivity.

The results here are obtained using a tractable and fairly standard demand system. The extent to which the results established in this paper are robust to using a richer demand system is ultimately an empirical question. However, it is clear that independent of a specific demand system, the resulting productivity estimates do change quite drastically if one is no longer ignorant about the product level and the degree of product differentiation in an industry, and how these factors differ over time and firms.

I analyze the impact of trade liberalization on firm performance using the method developed in this paper. Trade liberalization is measured by the abolishment of quota restricted imports and by increased levels of maintained quota. The quota restriction measures serve as additional variables to control for the unobserved price and the resulting estimates for productivity are therefore further purified from demand variation. While I find positive significant productivity gains from relaxing quota restrictions, the effects are estimated considerably lower than using standard productivity estimates. The latter still capture price and markup variation (across product segments and time) which are correlated with the change in demand conditions due to a change of trade policy, leading to an overestimation of productivity gains from opening up to trade.

Appendix A: The Belgian textile industry and the quota dataset

A.1 The Belgian textile industry:

I present the structure of the different segments, sub-segments and the products in my dataset in Table A.1. The different levels are important to structure the regressions and serve as additional sources of variation to identify demand parameters. The number in parentheses indicates the number of subsegments within a given segment whereas the last row indicates the number of products within a given segment. I also estimated demand elasticities at the level of the subsegments, i.e. 52 different parameters.

Table A.1.: Segment Structure: Number of Subsegments and Products per Segment

Interior (9)	Clothing (18)	
	Fabrics	Knitwear
Bed linen	Accessories	Accessories
Carpets	Baby clothes & children's	Babies' wear
Kitchen linen	Men's wear	Bath
Mattress ticking	Nightwear & underclothing	Children's wear
Table linen	Others	Fabrics for ...
Terry toweling articles	Rain-, sportswear & leisure	... Nightwear
Trimming	Women's wear	... Outerwear
Upholstery & furnishing fabr.	Workwear & protective suits	... Sportswear
Wallcoverings		Stockings- tights- socks
		Underwear
19	61	36

Technical (9)	Finishing (7)	Spinning (9)
Agrotech	Carpeting	Blended aramid, polyamid or polyacrylic
Buildtech	Knitted fabrics	Blended artificial yarns
Geotech	Material before spinning	Blended cotton or linen yarns
Indutech	NonWoven	Blended polyester yarns
Medtech	Woven fabrics	Blended polypropylene or chlorofibre yarns
Mobiltech	Yarns	Blended yarns
Packtech	Specialities	Filament Yarns
Protech		Spun Yarns (> 85% of 1 fibre)
Sporttech		Synthetic Fibres
231	132	84

A.2. Producer prices and demand elasticity

As mentioned in the text a producer price index is obtained by taking a weighted average over a representative number of products within an industry, where weights are based on sales (market shares). In the case of Belgium the National Institute of Statistics (NIS) gathers monthly information of market relevant prices (including discounts if available) of around 2,700 representative products (an 8 digit classification - PRODCOM - where the first 4 are indicating the NACEBELCODE). The index is constructed by using the most recent market share as weights based on sales reported in the official tax filings of the relevant companies. The relevant prices take into account both domestic and foreign markets and for some industries both indices are reported. I present unit prices at the 3 digit NACEBELCODE (equivalent to 4/5 digit ISIC code). I constructed these by dividing total value of production in a given subcategory by the quantity produced. Table A2 gives the PPI for the various subcategories with 1994 as base year except for the 175 category (Other textile products, mainly carpets). I do not use these to deflate firm-level revenues since I have no information in which category (ies) a firm is active since the product classification cannot be uniquely mapped into the NACEBELCODE and firms are active in various subcategories. The codes have the following description: *171*: Preparation and spinning of textile fibres, *172*: Textile weaving, *173*: Finishing of textiles, *174*:.Manufacture of made-up textile articles, except apparel, *175*: Manufacture of other textiles (carpets, ropes, ...), *176*: Manufacture of knitted and crocheted fabrics and *177*: Manufacture of knitted and crocheted articles.

Table A.2.: Producer Prices (Unit Prices) at Disaggregated Level

	171	*172*	*173*	*174*	*175*	*176*	*177*
1994	100	100	100	100	-	100	100
1995	99.4	96.7	110.4	111.0	-	100.9	100.7
1996	100.9	94.5	101.1	117.9	100	103.4	94.8
1997	103.7	94.5	101.3	108.5	99.2	93.9	97.5
1998	102.8	96.0	108.0	117.6	101.5	93.3	97.6
1999	95.0	95.8	100.6	118.2	99.6	94.8	92.9
2000	94.3	94.6	119.3	106.2	102.0	84.1	95.5
2001	96.7	93.2	108.4	107.7	104.1	86.9	101.3
2002	97.3	94.2	110.7	103.1	107.2	85.8	106.1
demand elasticity	-5.4675		-3.0628	-3.0628	*n.a.*	*n.a.*	-3.6470

Several observations are important to note. Firstly, there is considerable variation across subcategories of the textiles industry in terms of price changes over the period 1994-2002. The sector *Manufacture of knitted and crocheted fabrics* (176) has experienced a severe drop in output prices (14.2 percent) over the sample period, whereas the output prices in the *Finishing of Textiles* (173) has increased with more than 10 percent. Secondly, the evolution in the various subcategories is not smooth, periods of price increases are followed by decreases and the other way around. Thirdly, most of the price decreases occur at the end of the nineties when imports from Central and Eastern Europe were no longer quota restricted as agreed in the Europe Agreements. It is interesting to note that the segment (Spinning) with the most elastic demand (-5.3135) has indeed experienced a negative price evolution (2.7 percent). The latter segment also captures weaving activities which in turn also experienced a price decrease (5.8 percent). The segment (Finishing) with the least elastic demand (-3.2051) has had a sharp increase in its output prices (10.7 percent). The estimated demand elasticities from Table 5 are given in the last row for those subcategories I could map into segments.

A.3. Unobserved demand shocks and estimating production function

Formally, I relax the assumption that investment only depends on the capital stock and the unobserved productivity shock. I now have two unobservables (ω_{it}, ξ_{it}) and the investment function is now $i_{it} = i_t(k_{it}, \omega_{it}, \xi_{it})$. The demand unobservable ξ_{it} is assumed to follow a Markov process that is independent of the productivity process. We now need a second control s_{it} - say advertisement expenditures - to proxy the unobservable in order to control for the productivity shock. I denote the bivariate policy function determining (i_{it}, s_{it}) as $\Upsilon(.)$ and assume it is a bijection in (ω_{it}, ξ_{it}) conditional on the capital stock k_{it}

$$\begin{pmatrix} i_{it} \\ s_{it} \end{pmatrix} = \Upsilon_t(k_{it}, \omega_{it}, \xi_{it}) \tag{A.1}$$

As Ackerberg and Pakes (2005) show this allows us to invert and rewrite the unobservable productivity as a function of the controls in the following way

$$\widetilde{\omega}_{it} = \Upsilon_t^{-1}(k_{it}, i_{it}, s_{it}) \tag{A.2}$$

The revenue generating production function is as before and the first stage of the estimation algorithm now looks as follows

$$\begin{aligned} \widetilde{r}_{it} &= \beta_0 + \beta_l l_{it} + \beta_m\, m_{it} + \beta_k k_{it} + \beta_\eta q_{It} + \Upsilon_t^{-1}(k_{it}, i_{it}, s_{it}) + u_{it} \\ &= \beta_0 + \beta_l l_{it} + \beta_m\, m_{it} + \beta_\eta q_{It} + \widetilde{\phi}_t(k_{it}, i_{it}, s_{it}) + u_{it} \end{aligned} \tag{A.3}$$

where $\widetilde{\phi}_t = \beta_k k_{it} + \Upsilon_t^{-1}(k_{it}, i_{it}, s_{it})$. The non parametric function is in three variables, investment, capital and an additional control, where the latter controls for the unobserved demand shocks ξ_{it}. In addition to the standard Olley and Pakes (1996) methodology I control for both observed and unobserved demand shocks coming from the use of revenue in stead of physical output and from the notion that demand shocks might have an impact on the level of investments.

The second stage hardly changes compared to (13) since the process of the demand shock is assumed to be independent of the productivity shock. Consider the revenue generating production function at time $t+1$

$$\widetilde{r}_{it+1} = \beta_0 + \beta_l l_{it+1} + \beta_m\, m_{it+1} + \beta_k k_{it+1} + \beta_\eta q_{It+1} + E(\widetilde{\omega}_{it+1}|I_t) + v_{it+1} + u_{it+1}$$

where I have used the fact that productivity and the demand shock follow a first-order Markov process, i.e. $\widetilde{\omega}_{it+1} = E(\widetilde{\omega}_{it+1}|\widetilde{\omega}_{it}) + v_{it+1}$, where v_{it+1} is the news term. The capital coefficient is estimated as before where the only difference is that the estimate for $\widetilde{\phi}(.)$ is different compared to the standard case (12) and leads to more precise estimates for the capital stock.

$$\widetilde{r}_{it+1} - b_l l_{it+1} - b_m\, m_{it+1} - b_\eta q_{It+1} = \beta_0 + \beta_k k_{it+1} + \widetilde{g}(\widehat{\widetilde{\phi}}_{it} - \beta_k k_{it}) + e_{it+1} \tag{A.4}$$

where $e_{it+1} = v_{it+1} + u_{it+1}$. Variation in output purified from variation in variable inputs and observed demand shock that is correlated with the (observed) control s_{it} is no longer potentially contributed to the variation in capital.

In the previous section I collapsed productivity and quality into one unobservable $\widetilde{\omega}_{it}$. Note that here it implies that I include variables proxying for the quality unobservable (like advertisement expenditures, product dummies as suggested in section 5.2.2.) which take out additional variation related to the demand side, leading to different estimates for ϕ_{it} in the $NLLS$ estimation. When estimating the capital coefficient in equation (A.4) the identifying assumption is that the demand shocks are independent of the productivity shocks.

When allowing for productivity to depend on unobserved demand shocks, I would no longer be able to identify the capital coefficient as the non parametric function $g\left[\phi_{it} - \beta_k k_{it}, \Upsilon_t^{-1}(k_{it}, i_{it}, s_{it})\right]$ depends on investment at time t. This leaves no more independent variation in the capital stock

to identify β_k as $k_{it+1} = (1 - \delta)k_{it} + i_{it}$. In fact the only way out is to assume either that this demand unobservable (such as quality) is uncorrelated with capital and ends up in the error term e_{it+1}.

In the Table A.3 I present estimates of product specific effects that are obtained by introducing product dummies to control for unobserved demand shocks in the demand system. I recover about 20 products that are estimated significantly different from zero. This implies that they differ significantly in their ξ_j values from their respective segment average under the identifying assumption that the investment policy function does not depend on unobserved demand shocks.

Table A.3 Product specific Lerner estimates (Specification (28))

Segment	Product	Product Specific Effects
Clothing	Rainwear, sportswear and leisure wear: Jackets	0.4686
	Rainwear, sportswear and leisure wear: Sportswear	0.3132
	Accessories - Labels	0.1985
Technical	Textile draining or irrigation	0.7184
	Technical sewing thread / Technical weaving	0.3458
	Canvas for film sets and theatre scenery	0.2386
	Technical textiles for papermaking industry	0.4897
	Textiles for medical care - Hospital linen	0.2432
	Upholstery fabrics for car seats	0.2760
	Upholstery fabrics for caravans seats (trailers)	1.4764
Finishing	Special Finishes: Mercerising	1.0276
	Special Finishes: Spotrepellent	0.5649
	Material before spinning : Cleansing	0.6877
	Woven fabrics: Flame retardant	1.8124
	Yarns Package dyeing	0.2928
	Yarns Sectional warping	0.3388
	Yarns Waxing	0.3829
Spinning	Blended artificial yarns CTA/PA	0.3476
	Filament Yarns - PA 6	0.3889

A.4. The quota data

The quota data comes straight from the *SIGL database* constructed by the European Commission (2003) and is publicly available on-line (http://sigl.cec.eu.int/). The quota data is provided using a specific product data classification, the MFA classification. In order to match this to the firm-level data I had to map the MFA classification code into the NACE rev.1 industry code through the PRODCOM classification. I do face the problem that the industry classification is more aggregated than the quota classification which can lead to measurement error in the quota restriction variable.

The 182 product categories used in the SIGL database with the relevant unit of measurement (kilograms or units) can be found on-line at http://trade.ec.europa.eu/sigl/products.html.

The list of 56 supplying countries facing a quota at some point during the period 1994-2002 on any of the 182 product categories are: *Albania, Argentina, Armenia, Azerbaijan, Bangladesh, Belarus, Bosnia-Herzegovina+Croatia, Brazil, Bulgaria, Cambodia, China, Czech Republic, Egypt, Estonia, Former Yug Rep of Macedonia, Georgia, Hong Kong, Hungary, India, Indonesia, Kazakstan, Kirghistan, Laos, Latvia, Lithuania, Macao, Malaysia, Malta, Moldova, Mongolia, Morocco, Nepal, North Korea, Pakistan, Peru, Philippines, Poland, Romania, Russia, Serbia and Montenegro, Singapore, Slovak Republic, Slovenia, South Korea, Sri Lanka, Syria, Taiwan, Tajikistan, Thailand, Tunisia, Turkey, Turkmenistan, Ukraine, United Arab Emirates, Uzbekistan, Vietnam.*

Finally, I present two examples that illustrate how the liberalization of trade occurred in the textile industry. I present the evolution of the quota level (level) and the actual fill rate (FR) for two products on imports from China and Poland, respectively.

Table A.4.: Two Examples of Decreased Quota Protection

	Example 1		Example 2	
Product	*Garments other knitted or crocheted*		*Bed linen, other than knitted or crocheted*	
Supplier	Imports from *China*		Imports from *Poland*	
Year	Level (x1000, kg)	FR (%)	Level (x 1000, kg)	FR (%)
1993	21,000	87.76	2,600	60.30
1994	21,630	99.04	2,730	96.19
1995	23,422	122.85	3,436	96.18
1996	24,125	92.92	3,787	89.14
1997	24,848	103.37	3,977	89.41
1998	25,594	109.00	*quota abolished*	
1999	26,362	104.46		
2000	27,153	99.50		
2001	27,968	109.81		
2002	30,349	105.18		
2003	32,932	105.12		

The table above clearly shows the detailed level of information that is available at each point in time for each product-supplier pair. The liberalization for *Bed linen* imported from Poland took place under the abolishment of the quota in 1998. Whereas for *Garments* from China, the increased competition came under the form of increased quota levels (by 88 percent). For both cases, the quota were binding over the span of the period that we study.

Appendix B: Production synergies

When aggregating the product-level production function to the firm-level, I have assumed that there are no cost synergies or complementarities in producing several products within one firm. However, we know that the textile sector captures both supplying (*Spinning* and *Finishing*) and applying segments (*Technical textiles*). Firms that produce both type of products can expect to potentially benefit from combining both activities (or more). Therefore, I relax the assumption on the production technology by introducing a parameter σ_{sr} capturing the complementarity in production of combining different products (here segments), where r and s are the different segments. More formally the aggregation from product-level production into firm-level is given by (B.1)

$$Q_i = (L_i^{\alpha_l} M_i^{\alpha_m} K_i^{\alpha_k}) \exp(\omega_i + \sum_{s=1}^{5} \sum_{r=s}^{5} \sigma_{sr} S_{isr} + u_i^q) \tag{B.1}$$

where S_{isr} is 1 if a firm i is active in both segment r and s and zero otherwise and σ_{sr} the corresponding coefficients. Proceeding as before, I obtain the following augmented production function (B.2).

$$\widetilde{r}_{it} = \beta_0 + \beta_l l_{it} + \beta_m\, m_{it} + \beta_k k_{it} + \beta_{np} np_{it} + \sum_{s=1}^{5} \beta_{\eta s} q_{st} S_{is} + \sum_{s=1}^{5} \sum_{r=s}^{5} \beta_{\sigma_{sr}} S_{isr} + \omega_{it}^* + u_{it} \tag{B.2}$$

The estimated segment demand elasticities are somewhat more negative, however, the same economic interpretations apply, i.e. Interior and Spinning are the most elastic segments (-6.81 and -6.76). I now present the estimated coefficients on the extra term S_{isr} in Table B.1.

Table B.1: Estimated Product Complementarity

$\beta_{\sigma_{sr}}$		s				
		1	2	3	4	5
	1	-0.37*	0.15**	*0.39**	0.04	0.35*
	2		-0.27*	*0.36**	0.08	0.06
r	3			-0.61*	*0.28**	*0.23**
	4				-0.39*	0.22*
	5					-0.41*

Note: * significant at 1% level, **: at 10% level

A positive sign on the coefficients in the table above reflects a (on average) higher output conditional on inputs and demand conditions for a firm active in any two given segments. Firms combining any activity with Technical textiles (3) generate a higher output. To obtain the entire firm relevant effect, we have to add up the relevant terms, e.g. for a firm active in segment 1 and 3: $-0.37 + 0.39 = 0.02$, suggesting gains from diversification. The latter is also reflected in the negative coefficients on the head diagonal. Note that here I only allow test for pair effects in contrast to estimating all potential combinations of segments (31 parameters) .

Appendix C. Alternative Proxy Estimators

As mentioned in Appendix A of Levinsohn and Petrin (2002) the LP methodology needs firms to operate in a competitive environment and take output and input prices as given in order for the intermediate input to be monotonic increasing in productivity to be able to invert the productivity shocks and proceed as in Olley and Pakes (1996). Models of imperfect competition on the output market do not satisfy those assumptions and the proof depends on the specific degree of competition. Melitz (2001) needs to assume that more productive firms do not set disproportionately higher markups than the less productive firms in order to use the LP procedure. The monotonicity needed in Olley and Pakes (1996) does not depend on the degree of competition on the output market, it just needs the marginal product of capital to be increasing in productivity.

I now discuss which additional assumptions one needs in the LP framework in order to allow for non price taking firms. As in LP consider the simple static maximization problem of the firm where the production function is given by $Q_i = f(L_i, m_i, \omega_i)$ where capital is a fixed input. The latter is consistent with the OP framework where the capital stock at period t is determined at $t-1$ through investment and the capital stock. The LP estimator - just like the OP procedure - crucially relies upon an invertibility assumption, i.e. demand for intermediate inputs has to be monotonic increasing in productivity. Their proof (Appendix A in Levinsohn and Petrin 2000) works under the assumption of a competitive setting where firms take both input and output prices as given. I now relax this assumption and allow for a more general setting and I show the extra assumption one has to make in order to use the LP approach in setting as discussed in the main text. The profit function of the firm is given by

$$\pi_i = p_i(Q)Q_i - p_L L_i - p_m m_i$$

I now drop the firm index i and the first order conditions for the inputs labor and materials are given below

$$
\begin{aligned}
f_L(L, m, \omega) &= p_L/p \\
f_m(L, m, \omega) &= p_m/p
\end{aligned}
$$

and assuming the existence of all second order derivatives, the LP approach works if demand for intermediate inputs are monotonic increasing in the productivity. Differentiating the FOC with respect to productivity (ω) and introducing the elasticity of demand $\eta = \frac{dQ}{dP}\frac{P}{Q}$ and $-\infty < \eta < 0$, I obtain the following system

$$
\begin{pmatrix} pf_{LL} + f_L{}^2(p_Q) & pf_{Lm} + f_L f_m(p_Q) \\ pf_{mL} + f_L f_m(p_Q) & pf_{mm} + f_m{}^2(p_Q) \end{pmatrix} \begin{pmatrix} \frac{\partial L}{\partial \omega} \\ \frac{\partial m}{\partial \omega} \end{pmatrix} = \begin{pmatrix} -pf_{L\omega} + f_L(p_Q)f_\omega \\ -pf_{m\omega} + f_m(p_Q)f_\omega \end{pmatrix}
$$

and we can use Cramer's rule to identify the sign of $\frac{\partial m}{\partial \omega}$ and establish conditions under which we can still invert the intermediate input demand function, where the sign of the denominator is always positive since we are working under the maximizing profit condition. Note that $p_Q = \frac{p}{Q}\frac{1}{\eta}$ which shows the extra assumptions we will need in order for the demand for intermediate inputs to be increasing in the productivity shock

$$sign\left(\frac{\partial m}{\partial \omega}\right) = sign\left(\left(f_{L\omega} + \frac{f_L f_\omega}{Q}\frac{1}{\eta}\right)\left(f_{mL} + \frac{f_L f_m}{Q}\frac{1}{\eta}\right) - \left(f_{LL} + \frac{f_L{}^2}{Q}\frac{1}{\eta}\right)\left(f_{m\omega} + \frac{f_m f_\omega}{Q}\frac{1}{\eta}\right)\right)$$

Compared to price taking scenario under which LP work, I have four new terms related to the degree of competition (η). In the case of price taking firms LP need the assumption that

$$f_{L\omega}f_{mL} > f_{LL}f_{m\omega} \tag{D.1}$$

whereas now we need

$$f_{L\omega}f_{mL}Q + \frac{1}{\eta}\left(f_{L\omega}f_L f_m + f_L f_\omega f_{mL}\right) > f_{LL}f_{m\omega}Q + \frac{1}{\eta}\left(f_{LL}f_m f_\omega + f_L{}^2 f_{m\omega}\right) \tag{D.2}$$

It is clear that the assumption under the general setting is somewhat more complicated, essentially introducing the markup ($\frac{\eta}{\eta+1} \geq 1$). Proceeding with the proof as in LP (2000) since (D.2) holds everywhere, it holds that

$$m(\omega_2; .) > m(\omega_1; .) \text{ if } \omega_2 > \omega_1$$

The intuition on the extra terms in equation (D.2) is that markups starts playing a role as also noted by Melitz (2001). To see this, consider equation (D.2) and label the terms in the inequality ad follows $A + B > C + D$. Note that $A > C$ is the sufficient assumption needed in the price taking scenario. Furthermore we know that $B > 0$ and it is generally hard to sign D, the condition (D.1) is now given by

$$f_{L\omega}f_{mL} - f_{LL}f_{m\omega} > \frac{1}{\eta}(D - B) \tag{D.3}$$

Although the exact conditions are not of interest here, this appendix has shown that relaxing the assumptions of the nature of competition on the output market, has an impact on the validity of the LP estimation algorithm through the invertibility conditions Note that the LP condition is a special case of D.3 where $\eta = -\infty$.

As mentioned in the text, recently Ackerberg et al. (2004) analyzed the various proxy estimators used in the literature (OP and LP) and verified how robust they are with respect to the timing of inputs that takes place in the production process. They study the underlying data generating process both proxy estimators assume to identify the production function coefficients. Based on their observation I verify whether my estimated demand parameters (markups) are at all sensitive to the underlying assumptions in the production process by using a modified OP estimator. I consider the results discussed in the main text (*baseline*) and compare them with the estimated markups obtained from a more flexible approach. The *flexible* approach essentially no longer takes a stand on whether all firms face the same factor prices, face unions and more importantly it no longer matters when the productivity shock enters in the timing of the inputs labor and material. The first stage is then reduced to the following regression

$$r_{it} = \beta_\eta q_{It} + \beta_{qr} q r_{it} + \phi_t(l_{it}, m_{it}, k_{it}, i_{it}) + u_{it} \tag{30}$$

Table C.1: Estimated Markups under Alternative Specifications

Specification	Industry	Segment specific				
		Interior	Clothing	Technical	Finishing	Spinning
Baseline	0.31	0.24	0.35	0.31	0.34	0.26
Flexible	0.34	0.12	0.17	0.17	0.17	0.12
Baseline + Trade protection	0.27	0.16	0.24	0.21	0.22	0.19
Flexible + Trade protection	0.22	0.10	0.12	0.13	0.14	0.10

Table C.1 above shows, the estimated demand parameters are well within the range of the less flexible model used in the main text. Note that the flexible approach described in this appendix allows for a general production function where productivity shocks are additive in the log specification and thus allows for flexible substitution patterns among inputs (such as the translog production function). However, in order to recover the production function parameters α, the similar assumptions used in the main text have to be imposed in the second stage of the Ackerberg et al. (2004) approach. The advantage of the flexible approach is that we can estimate the markups in a flexible way in the first stage as robustness check. The last two rows then give us the range of the estimated markups for a given segment, e.g. for the Interior segment the estimated markup lies between 0.16 and 0.10.

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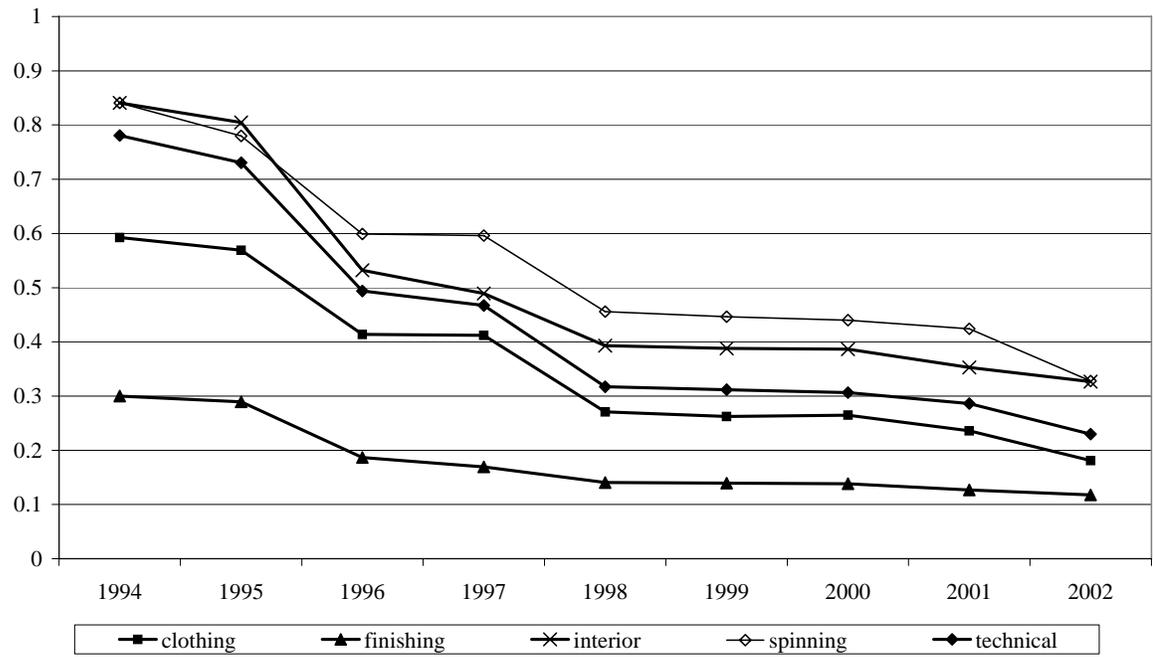
Figure 1: Evolution of Quota Protection Measure (qr) by Segment (1994-2002)

Table 1: Summary Statistics of Belgian Textile Industry

Year	Employment	Total Sales	Value Added	Capital	Materials	PPI
1994	89	18,412	3,940	2,443	13,160	100.00
1995	87	19,792	3,798	2,378	14,853	103.40
1996	83	18,375	3,641	2,177	14,313	99.48
1997	85	21,561	4,365	2,493	16,688	99.17
1998	90	22,869	4,418	2,650	17,266	98.86
1999	88	21,030	4,431	2,574	15,546	98.77
2000	90	23,698	4,617	2,698	17,511	102.98
2001	92	23,961	4,709	2,679	17,523	102.67
2002	99	26,475	5,285	2,805	17,053	102.89
Average	89	21,828	4,367	2,551	16,062	

Note: I report averages for all variables in thousands of euro, except for sales where I report total by year.

Table 2: Number of Firms and Production Structure Across Different Segments
Firms

	Interior	Clothing	Technical	Finishing	Spinning
Interior	*77.0*	4.8	15.8	7.3	1.8
Clothing		*58.9*	33.9	7.1	1.8
Technical			*35.1*	19.6	17.5
Finishing				*39.6*	12.5
Spinning					*47.5*
# firms	165	56	97	48	40

Note: The cells do not have to sum up to 100 percent by row/column, i.e. a firm can be active in more than 2 segments

Table 3: Number of Products and Production Structure Across Different Segments
Products

	Interior	Clothing	Technical	Finishing	Spinning
Interior	*83.72*	2.78	8.27	4.41	0.80
Clothing	3.03	*79.28*	15.36	1.86	0.48
Technical	7.01	8.97	*70.16*	9.06	4.79
Finishing	5.75	3.52	15.53	*72.85*	2.35
Spinning	3.72	0.65	27.20	7.40	*61.04*
median	2	6	8	11	9
min	1	2	1	2	1

Note: The cells do sum up to 100 percent by row. This table has to be read from the rows only.

Table 4: The Estimated Coefficients of the Production Function

	OLS	KG Level		KG Diff		OP	Augmented	
	[1]	[2]		[3]		[4]	[5]	
	β	β	α	β	α	β	β	α
labor	0.2300	0.2319	0.2967	0.2451	0.3338	0.2113	0.2126	0.3075
	(0.0095)	(0.0095)	(0.0316)	(0.0198)	(0.0343)	(0.0112)	(0.0112)	(0.0623)
materials	0.6298	0.6284	0.8041	0.5958	0.8115	0.6278	0.6265	0.9063
	(0.0074)	(0.0074)	(0.0770)	(0.0131)	(0.0519)	(0.0085)	(0.0084)	(0.1746)
capital	0.0879	0.0868	0.1111	0.0188	0.0256	0.0931	0.1037	0.1500
	(0.0072)	(0.0072)	(0.0137)	(0.0105)	(0.0143)	(0.0081)	(0.0063)	(0.0337)
output		0.2185		0.2658			0.3087	
		(0.0749)		(0.0462)			(0.1335)	
η		-4.58		-3.76			-3.24	
markup		1.28		1.36			1.45	
Nr Obs	1,291	1,291		1,291		985	985	

Note: β: estimated coefficients, α: production function coefficients.
Bootstrapped standard errors are given in parentheses.

Table 5: Estimated Demand Parameters and Implied Firm Elasticities

A: Estimated Demand Parameters						
		Interior	Clothing	Technical	Finishing	Spinning
	$\beta_{\eta s}$	0.1888*	0.2742*	0.2593*	0.3265*	0.1829*
No product dummies		(0.0742)	(0.1029)	(0.0907)	(0.1042)	(0.0774)
	$\eta_s \ (S_{is}=1)$	-5.2966	-3.6470	-3.8565	-3.0628	-5.4675
	$\beta_{\eta s}$	0.2315*	0.3140*	0.2952*	0.3178*	0.2437*
Product dummies		(0.0541)	(0.0756)	(0.0648)	(0.0756)	(0.0585)
(563 products)	$\eta_s \ (S_{is}=1)$	-4.3196	-3.1847	-3.3875	-3.1466	-4.1034
One Segment	$\beta_{\eta s}$	0.2641*	0.3550*	0.3575*	0.4563*	0.2556*
(667 obs)	η_s	-3.7864	-2.8169	-2.7972	-2.1915	-3.9124
>1 Segments	$\beta_{\eta s}$	0.1673*	0.2267*	0.2253*	0.2241*	0.1455*
(318 obs)	η_s	-5.9773	-4.4111	-4.4385	-4.4623	-6.8729

B: Implied Firm-Specific Demand Elasticities and markups		
	η	$\frac{\eta}{\eta+1}$
mean	-4.4486	1.3033
s.d.	0.6915	0.0676
minimum	-5.4059	1.2269
maximum	-3.1627	1.4624

Standard errors are given in parentheses and * denotes significance at 1 percent level.

Table 6: Number of Quota and Levels in Millions

| | Number of quota | *kg* | | *nr of pieces* | |
	protections	# quota	Level	# quota	Level
1994	1,046	466	3.10	580	8.58
1995	936	452	3.74	484	9.50
1996	824	411	3.70	413	7.95
1997	857	413	3.73	444	9.28
1998	636	329	4.21	307	9.01
1999	642	338	4.25	304	10.53
2000	636	333	4.60	303	9.77
2001	574	298	5.41	276	11.06
2002	486	259	5.33	227	12.37
change	-54%	-44%	72%	-60%	44%

Table 7: The Impact of Additional Demand Information: Quota Restriction

| | | Specification (28) | |
		without Quota Information	with Quota Information
	Interior	0.2426*	0.1643*
		(0.0589)	(0.0658)
	Clothing	0.3475*	0.2381*
Markups		(0.0821)	(0.0915)
β_{η_s}	Technical	0.3126*	0.2134*
		(0.0710)	(0.0796)
	Finishing	0.3364*	0.2219*
		(0.0824)	(0.0927)
	Spinning	0.2577*	0.1853*
		(0.0637)	(0.0690)
β_{qr}			-0.0886*
quota restriction			(0.0362)
β_l		0.2514*	0.2513*
		(0.0124)	(0.0123)
β_m		0.6785*	0.6808*
		(0.0100)	(0.0100)
β_k		0.0515*	0.0506*
		(0.0101)	(0.0122)
returns to scale		[1.30; 1.50]	[1.16; 1.30]

Note: * indicates significant at 1%

Table 8: Impact Trade Liberalization on Productivity

Specification (# obs)	Estimated coefficient	Productivity Estimated using	
		augmented model	OP
I (1,291)	qr	-0.0637**	-0.1068*
		(0.0366)	(0.0296)
II (1,088)	qr	-0.0430*	-0.0612*
		(0.0195)	(0.0193)
III (1,088)	$\triangle qr$	-0.0699*	-0.1254*
		(0.0312)	(0.0327)
IV (1,088)	$\triangle qr$	-0.1172*	-0.1605*
		(0.0374)	(0.0393)
	qr_{t-1}	-0.0468*	-0.0348*
		(0.0206)	(0.0216)
V (765)	$\triangle qr$	-0.0455**	-0.1347*
		(0.0272)	(0.0299)
VI (890)	qr	-0.0584*	-0.0664*
		(0.0229)	(0.0226)
	level	0.0019*	-0.0000
		(0.0008)	(0.0008)

Note: std errors in parentheses, * and ** denote significant at 5 or lower and 10 percent, resp.
All regressions include quota-product classification dummies (23 categories), except for VI.

Table 9: Productivity Impact of a 10 percent Decrease in Protection Measure

Productivity	Interior	Clothing	Technical	Finishing	Spinning	Overall
Augmented model	4.37	3.60	4.82	1.60	4.49	4.07
(1994-1997)	8.20	4.21	7.32	3.05	5.71	6.53
(1998-2002)	2.28	3.23	3.32	0.72	3.75	2.59
OP	8.06	6.45	8.63	2.86	8.04	7.28

Note: The figures are elasticities evaluated at the mean by segment over the relevant period.

Table 10: Change in Average Quota Level (1994-2002)

	Products measured in	
Supplying Country	kilograms	# pieces
Belarus	146	60
China	83	38
Hong Kong	62	49
India	56	127
Indonesia	90	78
Malaysia	58	66
North Korea	-	92
Pakistan	129	144
Peru	127	-
South Korea	61	69
Taiwan	36	28
Thailand	45	130
Uzbekistan	556	-
Vietnam	-92	55

Changes are expressed as a percentage.