Product Differentiation, Multi-Product Firms and Estimation of Productivity.

An Application to Trade Liberalization in the Belgian Textile Industry*

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Abstract

In this paper I propose a methodology to estimate (total factor) productivity in an environment of product differentiation and multi-product firms. In addition to correcting for the simultaneity bias in the estimation of production functions, I control for the omitted price bias as documented by Klette and Griliches (1996). By aggregating demand and production from product space into firm space, I am able to use plant-level data to estimate productivity. The productivity estimates are corrected for demand shocks and as by-products I recover the elasticity of demand and implied mark-ups. I apply this methodology to the Belgian textile industry using a dataset where I have matched firm-level with product-level information. The resulting production coefficients and productivity estimates change considerably once taking into account the demand variation and the product mix. Finally, I analyze the effects of trade liberalization in the Belgian textile industry. While I find significant productivity gains from trade liberalization, the estimated effects are approximately half of those obtained with standard techniques.

Key words: Productivity; Demand; Product mix; Trade liberalization

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1 Introduction

It is by now a well documented finding that periods of major changes in the operating environment of firms (e.g. trade liberalization, deregulation, etc.) are associated with productivity gains and that firms engaged in international trade (through export or FDI) are more productive.[1] The productivity measures are - mostly - recovered after estimating some form of a sales generating production function where output is proxied by (deflated) sales. This paper shows that these 'productivity measures' still capture price and demand shocks which are likely to be correlated with the change in the operating environment. This implies that the impact on 'actual productivity' cannot be identified which invalidates evaluation of the welfare implications.

I introduce a methodology for getting reliable estimates of productivity in an environment of imperfect competition in the product market and I allow for multi-product firms. I apply the suggested method to analyze the impact of the trade liberalization process in the Belgian textile industry on productivity. The underlying model is related to the original work of Klette and Griliches (1996), which discusses the bias in estimating a production function by using an industry-wide producer price index to deflate firm-level revenue as a proxy for output. Their focus is mainly on recovering the estimated returns to scale elasticity and there is no explicit discussion of the resulting productivity estimate. Furthermore, they rely on instrumental variables to correct for the simultaneity bias. The latter is a well documented problem when estimating a production function that inputs are likely to be correlated with unobserved productivity shocks and therefore lead to biased estimates of the production function. The recent literature on estimating productivity has focused mostly on controlling for the simultaneity problem, ignoring or assuming away the omitted price variable bias.[2]

Just like productivity, firm-level prices are not observed and therefore need to be controlled for. 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. 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 mark-ups and demand shocks.[3]

[1] Pavcnik (2002) documents the productivity gains from trade liberalization in Chile, Smarzynska (2004) finds positive spillovers from FDI in Lithuania and Van Biesebroeck (2006) 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] Some authors did explicitly reinterprete the productivity measures as sales per input measures. For instance see footnote 3 on page 1264 of Olley and Pakes (1996).

[3] 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

Some recent work has discussed the potential bias of ignoring this demand side when estimating production functions. 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. The estimation algorithm to obtain a measure for productivity relies on Bayesian estimation techniques. Melitz and Levinsohn (2002) assume a representative consumer with Dixit-Stiglitz preferences and they feed this through the Levinsohn and Petrin (2003) estimation algorithm. Foster, Haltiwanger and Syverson (2005) 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.[4]

I control for the simultaneity bias and introduce a demand system to control for unobserved prices. In addition, I allow for multi-product firms where I aggregate demand from product space into firm-level demand. I present a straightforward estimation algorithm that results in estimates for productivity that are consistent with multi-product firms and product differentiation. From this it follows that measured productivity increases need not to reflect (fully) an actual productivity increase as demand shocks and price effects are not filtered out. More specific, I combine the underlying structural framework of Olley and Pakes (1996) with a (modified version) of the demand system used in Klette and Griliches (1996). The latter suggests a way to identify a demand parameter from production data by essentially substituting the inversed demand function for the (unobserved) price. This approach corrects for the omitted price variable bias and results in unbiased coefficients of the production function. I introduce a rich source of product-level data matched to the production dataset that frees up the substitution pattern across products.

The methodological part of this paper is closely related to Melitz and Levinsohn (2002). There are, however, some important differences. Firstly, in addition to the plant-level dataset I have 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. Aside from a discussion of the methodology, I empirically show the bias in the production function coefficients and in the resulting

dynamic (oligopoly) games where productivity is a key primitive (Collard-Wexler, 2006).

[4] 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.

productivity estimates. Secondly, on top of correcting for the omitted price variable I control for the simultaneity bias using the Olley and Pakes (1996) procedure, where the unobserved productivity shock is proxied by a polynomial in investment and capital. The Olley and Pakes (1996) methodology is consistent with a dynamic optimization problem of a firm under uncertainty as suggested in Ericson and Pakes (1995). This structure turns out to be very instructive to deal with the bias of using sales to proxy for output and to evaluate how demand shocks can affect the productivity estimates. This does not rule out the use of alternative proxy estimators such as the estimator suggested by Levinsohn and Petrin (2003).[5]

Finally, I use the method suggested in this paper to analyze the productivity dynamics in the Belgian textile industry during a significant trade liberalization espisode using detailed product-level quota information. A large body of empirical work has studied the impact of various trade policy changes on productivity.[6] Essentially, the literature so far has established a strong relationship between opening up to trade and measures of sales-per-input. However, 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. In order to interprete the results in a welfare sense, one has to be willing to make more explicit assumptions on the nature of demand. Whereas in most of papers dealing with the estimation of firm-level productivity, the assumptions on the nature of demand are not mentioned and are often that all firms face the same price in a given industry. In addition, the method sheds light on other parameters of interest - such as markups and the elasticity of substitution - and the role of differences in product mix across firms.

The remainder of this paper is organized as follows. In section *II* the standard approach to estimate production functions is discussed. Furthermore, I introduce a demand system and show the bias on the production function coefficients. Section *III* introduces the estimation strategy and the potential bias of using standard productivity estimates to evaluate policy changes. The readers interested in the empirical application can skip section *III* and are referred to sections *IV- VI.* In section *IV*, I present the data that includes detailed product-level information in addition to a rich firm-level dataset of Belgian textile producers. In section *V* I present the coefficients of the production functions as well as the estimated parameters of the demand system. In section *VI* 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,

[5]The Levinsohn and Petrin (2003) estimator can be used, however, with some additional assumptions made on the relation between the unobserved productivity shocks and markups. See Appendix C for a discussion on this.

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

where the quota information serves as an additional control variable for the unobserved prices. The last section concludes.

2 Estimating Productivity Using Production Data

2.1 Identification of The Production Function Parameters

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

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

where Q stands for the quantity produced, L, M and K are the three inputs labor, materials and capital; and α_l, α_m and α_k are the coefficients, respectively.[7] The constant term α_0 captures the mean productivity and ε captures the economies of scale, i.e. $\varepsilon = (\alpha_l + \alpha_m + \alpha_k)$. Productivity is denoted by ω and u^q is an *i.i.d.* component. Below I aggregate over different products within a firm and I assume that the production structure is identical for every product j and therefore no cost synergies or spill overs are modelled here (see Appendix B for more on this).

The standard approach in identifying the production function coefficients starts out with a production function as described in equation (1). The physical output Q is then substituted by deflated revenue ($\widetilde{R}$) using an industry price deflator (P_I). 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 structural estimation of productivity has worried about the correlation between the chosen inputs x and the unobserved productivity shock ω. 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

[7] 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.

mentioned in Klette and Griliches (1996) inputs are likely to be correlated with the price a firm charges.[8] The error term $(u^q + p_{it} - p_{It})$ 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 most straightforward correlation goes as follows: the level of inputs are positive correlated with the firm's output, which is negatively correlated with the price. Therefore firm-level inputs (materials and labor) are negatively correlated with the unobserved price and thus underestimates the coefficients on labor and materials. This is referred to as the omitted price variable bias. This bias works in the opposite direction as the simultaneity bias - the correlation between the unobserved productivity shock (ω) and the inputs (x) - making any 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 prices will be passed through a higher output price if output markets are imperfect, the extent of this pass through depends on the relevant mark-up. 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.[9]

2.2 Introducing Demand: Product Differentiation and Multi-Product Firms

I now introduce the demand system that firms face in the output market. The demand system is based on the standard horizontal product differentiation model and allows for an unobserved quality component. 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 per se, as long as the inverse demand system can generate a (log-) linear relationship

[8] 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).

[9] 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 $(m_i + p_i^m - p_I^m)$.

of prices and quantities. What follows then also holds for other demand systems and later on I will turn to some alternative specifications. The inverse demand system is then used to substitute for the unobserved price variable in the revenue generating production function. 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}

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

where Q_{It} is the industry output at time t, (P_{it}/P_{It}) the relative price of firm i with respect to the average price in the industry, u^d is an idiosyncratic shock specific to firm i and η is the substitution elasticity between the differentiated products in the industry, where $-\infty < \eta < -1$. 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.[10]

The firms are assumed to operate in an industry characterized by horizontal product differentiation, where η captures the substitution elasticity among the different products 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. I refer to Berry (1994) for more on demand in industries with product differentiation. It is clear that the demand system is quite restrictive and implies one single elasticity of substitution for all products within a product range and hence no differences in cross price elasticities. In the empirical application the elasticity of substitution is allowed to differ among product segments. However, in most productivity studies the demand side is ignored and productivity is interpreted as an output per input measure (Katayama et al , 2003). The motivation for modeling demand explicitly here is

[10] In the empirical analysis 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). 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.

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.

Taking logs of equation (4) and writing the price as a function of the other variables results in the following expression where $x = \ln X$

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

As discussed extensively in Klette and Griliches (1996) and Melitz and Levinsohn (2003), the typical firm-level dataset has no information on physical output per firm and prices.[11] Commonly, we only observe revenue and we deflate this using an industry-wide deflator. As discussed above, deflating the revenue by an industry-wide price deflator is only valid if firms have no price setting power and all face the same price. The observed revenue r_{it} is then substituted for the true output q_{it} when estimating the production function. Ignoring the price thus leads to an omitted variable bias since it is not unlikely that a firm's price is correlated with the used inputs. 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 ($\widetilde{r}_{it} = r_{it} - p_{It}$)

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

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.

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

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. The estimated coefficients are estimates of a reduced form combining the demand and supply side in one equation.

I now further decompose the unobservable u^{d} in equation (4) into an unobserved quality (ξ) and an *i.i.d.* component to allow for unobserved firm (product) effects that impact demand. This leads to my general estimating equation of the revenue production function

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

[11] 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.

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 (ε) 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 mark-up $(\frac{\eta}{\eta+1})$. When correcting for the simultaneity bias I follow the Olley and Pakes (1996) procedure and replace the productivity shock ω 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 in more structure on the demand side, e.g. allowing the demand elasticity to vary across different segments and proxy for unobserved quality (ξ) using product dummies. Bringing 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).

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.

2.2.2 Multi-Product Firms

I now allo firms to produce multiple products, where η still captures the substitution elasticity among the varieties. For now I do not allow for different substitution patterns among products owned by a single firm as opposed to the substitution between products owned by different firms. The modelling approach here does allow for more realistic substitution patterns in the spirit of Berry, Levinsohn and Pakes (1995) among the various products produced and ultimately will be determined by the data at hand.

The demand system is identical to the one expressed in equation (4), only a product subscript j is added. Note that the demand is not relevant at the product space M. There are N firms and M products in the industry with each firm producing M_i products, where $M = \sum_i M_i$.[12] 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.

$$Q_{ijt} = Q^s_{It} \left(\frac{P_{ijt}}{P^s_{It}} \right)^{\eta_s} \exp(u^d_{ijt} + \xi_{ijt}) \tag{8}$$

The demand for product j of firm i is given by Q_{ij}, Q^s_I is the demand shifter relevant at the product-level, P^s_I is the industry price index relevant at the product level, η_s is the demand elasticity relevant at the product space, ξ_{ijt} is unobserved product quality and u^d_{ijt} is product j specific idiosyncratic shock.[13] The elasticity of demand η_s is now specific to a given product segment s of the industry.

As mentioned above, the working assumption throughout his 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}

$$r_{ijt} - p^s_{It} = \left(\frac{\eta_s + 1}{\eta_s} \right) x_{ijt}\alpha - \frac{1}{\eta_s} q^s_{It} + \left(\frac{\eta_s + 1}{\eta_s} \right) (\omega_{ijt} + u^q_{ijt}) - \frac{1}{\eta_s}\xi_{ijt} - \frac{1}{\eta_s} u^d_{ijt} \tag{9}$$

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. 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

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

[13] 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.

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 simplicity 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

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

where I have 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 $np_{it} = \ln(M_{it})$. Productivity and quality 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).[14] Furthermore q_{It} is the demand shifter captured by the industry output and it turns out to be firm specific if one allows the demand elasticity to differ across products or segments of products. The latter is a result of firm specific product mixes and therefore each firm faces a (potential) different total demand over the various products it owns. In the case of a constant elasticity of demand across products (segments) and single product firms, this term is as before ($\beta_\eta q_{It}$).

The two unobservables - productivity and quality - can be related to the information of the product data. The terms ω_{it} and ξ_{it} capture productivity and quality shock over the various products, respectively. The firm specific productivity (quality) shock can be interpreted as an average - across the M_i products - productivity (quality) shock where I assume that the number of products per firm are constant over time.

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 quality shock (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 of the potential miss-measured productivity growth using the standard identification methods.

[14] Foster, Haltiwanger and Syverson (2005) 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.

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.[15] I group the two unobservables productivity ω and quality ξ into 'one unobservable' $\widetilde{\omega}$. 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 quality and productivity component follow the same stochastic process, i.e. a first order Markov process.[16] 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, 2004).[17] Both productivity and quality are known to the firm when making its decision on the level of 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, $\widetilde{\omega}$, 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 $\widetilde{\omega}$ containing both quality and productivity. However, it does not change the impact on investment. A firm draws a shock consisting of both productivity and quality 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 increased quality perception of its product(s). We could even interpret investment in a broader sense, both as investment in capital stock and advertizing. 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

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

[15] 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.

[16] 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.

[17] 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.

under the identifying assumption that the function in capital and investment proxies for the unobserved product/quality shock.[18] Note that the $\phi(.)$ 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 improves the proxy of this complicated function by introducing demand variables in the first stage. The identification of the capital coefficient in a second stage will also improve due to the estimate for $\phi(.)$ out of the first stage.

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.

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

where b is the estimate for β out of the first stage. Note that here I need to assume that quality and productivity follow the exact same Markov process in order to identify the capital coefficient. If the quality term does not follow the same process and is depending 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. Another way out is to assume that the quality shock is uncorrelated with capital and has no lag structure, but that would leave us back in the case where quality 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 (tfp) is then recovered as the residual by replacing the true values by the estimated coefficients, $(\widetilde{r}_{it} - b_l l_{it} - b_m\, m_{it} - b_k k_{it} - b_\eta q_{It})\,\frac{\widehat{\eta}}{\widehat{\eta}+1} = \widehat{tfp}_{it}$.

The suggested framework does not rule out alternative proxies for the unobserved productivity shock. Levinsohn and Petrin (2003) use intermediate inputs as a proxy.[19] 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

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

[19]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).

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.[20] In addition, 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.[21]

3.2 Unobserved Quality and Productivity

So far I have assumed that the unobservable $\widetilde{\omega}$ - including both productivity and quality - can be proxied by a non parametric function in investment and capital. The underlying assumption here is that investment proxies both the shocks in productivity (ω) and product quality (ξ). I now relax this by allowing investment to depend on another unobservable - a demand shock - that 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 quality itself would not enter the production function if we would observe physical output or firm-level prices in the case where quality does not enter the investment policy function. 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. The case discussed here has a demand shock entering both through the productivity shock and through the use of revenue to proxy for output at the firm level. If the unobserved quality shock does not enter the policy function I can just control for it in the first stage of the regression just like the demand shifter Q_I and this leads to a different estimate for the non parametric function $\phi(.)$. The details of the estimation thus depend on whether quality is allowed to enter both the demand and the investment function. If not, then the ϕ function is different from before by subtracting the additional product dummy terms. For the remainder of the paper I will allow for the quality unobservable to impact the investment decisions, which implies that the estimates on the product dummies (if of any interest) are only recovered in the final stage of the estimation algorithm.

[20] However, if the estimates are precise and if the bias goes in the direction as predicted by the theory (overestimation of the labor coefficient), which is the case in almost all empirical applications of both OP and LP, than the theoretical case raised by Ackerberg et al. (2004) is not backed by the data. I would like to thank Amil Petrin for pointing this out to me.

[21] Also see De Loecker (2004) where this test is implemented and the labor coefficient is found to be insignificant throughout all specifications when running $\widetilde{r}^{*}_{it+1} = c + \beta_k k_{it+1} + g(\widehat{\phi}_t - \beta_k k_{it}) + \beta_c l_{it} + e_{it+1}$.

Formally, I relax the assumption that investment only depends on the capital stock and the unobserved productivity shock. I now have two unobservables (ω, ξ) and the investment function is now $i_{it} = i_t(k_{it}, \omega_{it}, \xi_{it})$. The demand unobservable ξ is assumed to follow a Markov process that is independent of the productivity process. We now need a second control s_{it} - say advertizement 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}

$$\begin{pmatrix} i_{it} \\ s_{it} \end{pmatrix} = \Upsilon_t(k_{it}, \omega_{it}, \xi_{it}) \tag{14}$$

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

$$\widetilde{\omega}_{it} = \Upsilon_t^{-1}(k_{it}, i_{it}, s_{it}) \tag{15}$$

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

$$\begin{aligned} \widetilde{r}_{it} &= \beta_0 + \beta_l l_{it} + \beta_m m_{it} + \beta_k k_{it} + \beta_\eta q_{It} + \Upsilon_t^{-1}(k_{it}, i_{it}, s_{it}) + u_{it} && (16) \\ &= \beta_0 + \beta_l l_{it} + \beta_m m_{it} + \beta_\eta q_{It} + \widetilde{\phi}_t(k_{it}, i_{it}, s_{it}) + u_{it} && (17) \end{aligned}$$

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. 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 $t+1$

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

where I have used the fact that productivity and the demand shock follow a first-order Markov process, i.e. $\widetilde{\omega}_{it+1} = E(\widetilde{\omega}_{it+1}|\widetilde{\omega}_{it}) + \upsilon_{it+1}$, where υ 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.

$$\widetilde{r}_{it+1} - b_l l_{it+1} - b_m m_{it+1} - b_\eta q_{It+1} = \beta_0 + \beta_k k_{it+1} + \widetilde{g}(\widehat{\widetilde{\phi}}_{it} - \beta_k k_{it}) + e_{it+1} \tag{18}$$

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.

Before I have combined productivity and quality into one unobservable $\widetilde{\omega}$. Note that here it implies that I include variables proxying for the quality unobservable (like advertizement expenditures, product dummies as suggested in section 5.2.2.) which take out additional variation related to the demand side (ξ), leading to different estimates for ϕ in the $NLLS$ estimation. When estimating the capital coefficient in equation (18) the identifying assumption is that the demand shocks are independent of the productivity shocks.

In order to allow quality to be independent from the productivity shock and thus evolve differently over time, I would no longer be able to identify the capital coefficient as the non parametric function $(g(\phi_{it} - \beta_k k_{it}, \Upsilon_t^{-1}(k_{it}, i_{it}, s_{it})))$ depends on investment at time t. In fact the only way out is to assume either that this quality unobservable is uncorrelated with capital and ends up in the error term e

3.3 Potential Biases of Using Standard Productivity Estimates

In order to compare with the standard regression with single product firms, it is clear that when estimating equation

$$\widetilde{r}_{it} = \beta_0 + \beta_l l_{it} + \beta_m m_{it} + \beta_k k_{it} + tfp_{it} + u_{it} \tag{19}$$

that the resulting productivity estimate (residual) has to be corrected for i) the number of products a firm produces and ii) the demand parameter, on top of the potentially differently estimated coefficients β_l, β_m, β_k and β_0 For now I assume away the unobserved quality component and focus on the unobserved productivity shock. The resulting measured productivity tfp relates to the true unobserved productivity ω_{it} in the following way

$$\omega_{it} = (tfp_{it} - \beta_\eta q_{It} - \beta_{np} np_{it}) \left(\frac{\eta}{\eta + 1} \right) \tag{20}$$

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 (20) 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 (e.g. trade liberalization/ protection).

In a more general framework of time varying number of products per firm (M_{it}) the bias in measured productivity tfp is given by (21). The traditional measure tfp captures various effects in addition to the actual productivity shock ω.

$$tfp_{it} = \beta_{\eta_t} q_{It} + \beta_{np_t} np_{it} + \left(\frac{\eta_t + 1}{\eta_t}\right) \omega_{it} + \frac{1}{|\eta_t|} \xi_{it} \tag{21}$$

Measured productivity consists of a pure demand specific term ($\beta_\eta q_{It}$) and is related to the number of products, in addition to productivity and quality interacted with the inverse of the mark-up and the Lerner index, respectively.

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.[22] In terms of my framework, this measure of opening up to trade might also capture changes in the mark-up (through change in elasticity of demand) and the product mix of firms. Similar studies have essentially measured productivity in some form as expressed in equation (21). The increased (measured) productivity can be driven by four factors: i) increased product quality, ii) increased productivity, iii) more elastic demand and iv) increased number of products.

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.[23] Even in the case of single product firms measured pro-

[22] 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).

[23] Harrison (1994) builds on the Hall (1988) methodology to verify the impact of trade reform on

ductivity growth (Δtfp_{it}) captures demand shocks and changes in mark-up. Using equation (21) and assuming that firm i experienced no productivity gain at all ($\omega_{it} = \omega_{it-1}$) it is clear that we can still measure a productivity increase. 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 tfp

$$tfp_{it} = \delta_0 + \delta_1 d_{it} + z_{it}\lambda + \varepsilon_{it} \tag{22}$$

where z_{it} captures a vector of control variables and ε is an *i.i.d.* error term. Using expression (21) it is straightforward to verify the different sources of correlation that bias the estimate for δ_1

$$\frac{\partial E(tfp_{it})}{\partial d_{it}} = \frac{\partial E((q_{It} + \xi_{it})/|\eta_t|)}{\partial d_{it}} + \frac{\partial E(np_{it})}{\partial d_{it}} + \frac{\partial E((\eta_t + 1)/\eta_t)\omega_{it}}{\partial d_{it}} \tag{23}$$

where the expectation is conditional upon z_{it}. It is clear that impact of d_{it} on productivity (ω) 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 bias in the coefficient of interest, δ_1.

Note that on top of the bias the point estimate of the productivity effect is multiplied by the inverse of the (firm specific) mark-up. Konings and Vandenbussche (2005) showed that markups increased significantly during a period of trade protection after antidumping filings in various industries. The second term 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 turn to the bias in evaluating the impact of decreased quota protection in the Belgian textile industry on estimated productivity in section *V*.

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

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*".

in quota protection. My data capture the Belgian textile industry for the period 1994-2002. The firm-level data are made available by the National Bank of Belgium and are 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 has information on entry and exit.

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. They split up the textile industry into 5 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. From this source I was able to link firms with the number of different products they produce, including other information on the different segments of the textile industry.

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.[24] 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.[25]

From the BELFIRST dataset I have virtually the entire population of textile producers and this allows me to check for sample selection and sample representativeness. The entry and exit data are detailed in the sense that I know when a firm exits and whether it is a 'real economic exit', i.e. not a merger, acquisition or a break up into other firms.

By adding the rich source of product-level data (FEBELTEX), 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 in the 17 listings. It is therefore important to take

[24] 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.

[25] 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 as well as suggested in Olley and Pakes (1996) and 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.

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 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 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.).

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.

Together with the 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 specificly.[26] 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

[26] 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 V I analyze the productivity dynamics during this increased competition period.

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.

To every firm present in this dataset I have matched 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 informative and ties up with a recent series of papers by Bernard et *al.* (2006) looking at the importance of differences in product mix across firms. Table 2 presents a matrix where each cell denotes the percentage of firms that is active in both segments.

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

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. This information is very interesting in itself, since it gives us some information about the product mix and product diversification. 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.

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.

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.

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).

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 change are underestimated. Furthemore, I allow for segment specific elasticity of substitution parameters and introduce product fixed effects to further control for unobserved demand shocks.

5.1 The Estimated Coefficients

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 difference 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.

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.
Standard errors are given in parantheses.

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 bigger 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).[27]

The estimated coefficient on the industry output variable is highly significant in all specifications and is a direct estimate of the Lerner index and the implied elasticity of demand and the implied mark-up is also given. Moving across the various specifications, the estimate of the average Lerner index (or the mark-up) 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 proxied 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 mark-up. The implied demand elasticities are around -3 and the estimated mark-up is around 1.4.[28] 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 mark-ups from firm-level production data.

[27] 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 balanced panel (0.0879), suggesting that the sample of matched firms is not a particular set of firms.

[28] 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 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.

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 e.g. labor. The industry output variable captures variation over time of total deflated revenue and as Klette and Griliches (1996) mentioned 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. 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_i).

In the next section I use the product-level information that allows for firm specific demand shifters as firms have different product portfolios over the various segments of the industry. Potentially, estimated productivity is different due to different estimated parameters (β) and additional terms (*industry output*) 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) are not expected to change much once more demand information is introduced since they capture both demand and production variation, the implied production function parameters (α) however will change.

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-firm specific shocks, essentially proxying 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

The demand parameter is freed up to be segment-specific by interacting the segment demand shifter (segment output) with the segment share variables.[29] The share variable S_{is} is the fraction of firm i 's products in segment s (M_{is}) in the firm's total number of products ($M_i = \sum_s M_{is}$), where $s = \{1$ (*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. As was shown in Tables 3 and 4, using the product information revealed a pattern of activity concentration into one segment on average, however there is quite some variation across firms.[30]

I now turn back to the general setup of the paper with multi-product firms. The demand for every product is given by (8) and q_{st} captures the product specific demand shifter. As in the single product firm case I proxy the demand shifter by output, however, now it is segment output. The segment output I consider is constructed in the following way. I observe firm-level revenue r_{it} and I know the share of the firm's products per segment in its total products produced (S_{is}). I consider the revenue of firm i in segment s to be $R_{ist} = R_{it} S_{is}$ with $S_{it} = M_{is}/M_i$. That is, if a firm has 20 percent of its products in segment 1 (Interior Textiles) I assume that 20 percent of its revenue comes from that segment. The relevant weight to construct the segment output is $v_{ist} = \frac{R_{ist}}{\sum_i^{N_s} R_{ist}}$, where N_s is the number of firms active in segment s. The segment output q_{st} is then proxied by $\sum_i v_{ist} \widetilde{r}_{ist}$ as before. I now introduce these terms interacted with the segment share variable in the augmented production function and estimate the following regression

$$\widetilde{r}_{it} = \beta_0 + \beta_l l_{it} + \beta_m m_{it} + \beta_k k_{it} + \left(\sum_{s=1}^{5} \beta_{\eta_s} q_{st} S_{is} \right) + \beta_{np} np_{it} + \omega_{it}^* + u_{it} \tag{24}$$

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

[29] I have also estimated demand relevant parameters one level deeper, see Appendix A.1 for the structure of the segments. However, this leads to a model with 51 different demand elasticities and identification is somewhat harder.

[30] 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., 2005) 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, it potentially biases the input coefficients.

the various segments in the textiles for those firms having all their products in one segment ($S_{is} = 1$).

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 (-0.0396), suggesting that firms with more products would look like they are more productive if we do not control for the fact that they have higher revenues because of selling several products.[31] 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 -5.2966. 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 η_i and mark-up 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.[32]

[31] I also used the number of segments and the results are similar.

[32] 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).

Table 5: Estimated Demand Parameters and Implied Firm Elasticities

		Interior	Clothing	Technical	Finishing	Spinning
A: Estimated Demand Parameters						
	$\beta_{\eta s}$	0.1888*	0.2742*	0.2593*	0.3265*	0.1829*
No product dummies		(0.0742)	(0.1029)	(0.0907)	(0.1042)	(0.0774)
	η_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)	η_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 mark-ups	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 parantheses and * denotes significance at 1 percent level.

5.2.2 Unobserved Product Characteristics

I now introduce product dummies to capture the product-firm specific demand shocks and time invariant quality unobservables (ξ_j). In terms of section 3.2 the product dummies proxy for the unobserved demand shock - quality - that is firm specific and potentially impacts the investment decision. I assume time invariant unobserved product characteristics. As mentioned above, 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 (25). The product dummies are captured by $\sum_{k=1}^{K} \lambda_k PROD_{ik}$ where $PROD_{ik}$ is a dummy variable being 1 if firm i has product k and λ_k are the relevant coefficients. Note that I introduce the product dummies motivating the need to correct for product specific demand shocks and unobserved quality. However, they will also capture variation related to the production side and those two types of variations are not separable.[33] The identifying assumption for recovering an estimate on the capital coefficient is that productivity and

[33] 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 a time variant quality component.

the quality 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 proxied by the industry output.

$$\widetilde{r}_{it} = \beta_0 + \beta_l l_{it} + \beta_m \, m_{it} + \sum_{s=1}^{5} \beta_{\eta s} q_{st} S_{is} + \beta_{np} np_i + \widetilde{\phi}_t \left(i_{it}, k_{it}, \sum_{k=1}^{K} \lambda_k PROD_{ik} \right) + u_{it} \quad (25)$$

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 time invariant quality differences, 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, the table above 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.[34] 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 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 mark-ups can be seen as a special case where own and cross elasticities of demand are restricted to be the same within a segment.

[34] Increased international competition in the Interior and Spinning segments is documented in section *VI* where quota protection is discussed.

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 lies in between and 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.[35] 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 and the research question at hand 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

In this section I introduce product-level quota restrictions as additional controls for the unobserved firm-level price variable in the augmented production function. In section 5 I showed that the industry output variable was highly significant, however, it implied rather high returns to scale estimates. Including the quota restriction variable is expected to lead to somewhat lower estimates on the industry output variable Q_I since firms protected by quotas are expected to have higher market share - if anything - and produce more, essentially correcting 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. Moreover, since quota tend to apply on countries with considerable lower wages and costs in producing textiles.

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 standard techniques in estimating productivity differ from the methodology suggested in this paper. Aggregate industry productivity might increase by

[35] 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.

the mere exit of lower productivity firms and/or the reallocation of market share towards more productive firms.[36]

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 quotas at the EU level are the relevant quotas 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.[37] From this I constructed a database listing product-country-year specific information on quotas 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. 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 8 below shows the number of quotas that apply for the sample period 1994-2002. In addition I provide the average quota levels split up in kilograms and number of pieces, both expressed in millions.

[36] As shown in Syverson (2004), demand shocks might in turn impact the aggregate productivity distribution.

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

Table 8: Number of Quota and Levels in Milions

	Number of quota protections	*kg*		*nr of pieces*	
		# quota	Level	# quota	Level
1994	1,046	530	3.10	478	8.58
1995	956	494	3.74	462	9.50
1996	826	416	3.70	410	7.95
1997	841	420	3.73	421	9.28
1998	656	319	4.21	337	9.01
1999	662	316	4.25	346	10.53
2000	656	315	4.60	341	9.77
2001	592	287	5.41	305	11.06
2002	486	235	5.33	266	12.37
change	-54%	-56%	72%	-44%	44%

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 quotas 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 quotas and the increase in the quota levels of existing quotas, points to a period of significant trade liberalization in 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 the quotas relevant for the various products by supplier 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

$$qr_{gt} = \sum_{e} a_{et} qr_{egt} \tag{26}$$

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 121 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 (27) and the number of quotas (nqr_{it}) that apply in a given industry l.

$$qr_{it} = \frac{1}{N_{gt}} \sum_{g \in l(i)} qr_{gt} \tag{27}$$

In Figure 1 I show the evolution of the quota restriction variable given by (27) 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 variables, i.e. it enters the demand system (4) through the shocks u^d and is not correlated with any of the production data variables.

6.2 Quota Restrictions and Productivity

I now introduce the average quota restriction qr_{it} and the number of quotas nqr_{it} into the unobserved part of the demand system.[38] 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)

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

where the term in parentheses captures the quota measures.[39] 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 9 presents the

[38] The interpretation of this model is to estimate the elasticity of subsitution (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. 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 in Table 10 are invariant.

[39] 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.

estimated Lerner indices (β_η) and compares them with the specification where the extra demand variation captured by the quota restriction ($\beta_{qr} qr_{it} + \beta_{nq} nqr_{it}$) 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 product specific Lerner estimates under the assumption that the investment decision does not depend on the unobserved demand shock. 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.[40]

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 very 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.

[40] 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.

Table 9: The Impact of Additional Demand Information: Quota Restriction

		Specification (28)	
		without Quota Information	with Quota Information
β_η	Interior	0.2426*	0.1643*
	Clothing	0.3475*	0.2381*
	Technical	0.3126*	0.2134*
	Finishing	0.3364*	0.2219*
	Spinning	0.2577*	0.1853*
	β_{qr}		-0.0886*
	β_l	0.2514*	0.2513*
	β_m	0.6785*	0.6808*
	β_k	0.0515*	0.0497*
	returns to scale	[1.30; 1.50]	[1.16; 1.30]

Note: * indicates significant at 1% and nqr is not significant

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 essentially establishing a highly significant positive correlation between productivity and opening up to trade.[41] 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 run impact on the efficiency of an economyt.

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

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

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

where $\widehat{\omega}$ 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 10 presents the estimates of δ_1 under various specifications.

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

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.[42] 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

[42] Using the estimates one can derrive 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).

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.

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 11 shows the impact of a 10 percent decrease in the quota restriction measure on productivity for the various segments and compares it with the results using 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.[43]

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 halfed) and this is what one would expect for firms operating in an advanced economy, as opposed to firms active in more developping 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.

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

Table 11: 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 elasticites evaluated at the mean by segment over the relevant period.

Furthermore in Table 11, 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 measure of relaxing quota restrictions is by increasing the level of existing quotas. 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 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 12 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 below 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 qr that picks up whenever a quota on a given product from a supplying country is abolished.

Table 12: 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.

In order to verify the impact of increased quota levels - in addition to the abolishment of quotas - I include a variable that measures the total level of quotas (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 quotas 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.

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 apply the suggested methodology to analyze the impact of trade liberalization on firm performance where trade liberalization is measured by the abolishment of quota restricted imports and by increased levels of maintained quotas. The quota restriction measures serve as additional variables to control for the unobserved price and the resulting estimate for productivity is 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 mark-up 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
Matress 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. Product Specific Lerner Estimates (Specification (28))

Segment	Product	Product Lerner Index
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 occured 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.

Appendix C. Invertibility Conditions.

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 mark-ups 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

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

It is clear that the assumption under the general setting is somewhat more complicated, essentially introducing the mark-up ($\frac{\eta}{\eta+1} \geq 1$). Proceeding with the proof as in LP (2000)

$$\int_{\omega_1}^{\omega_2} \frac{\partial m}{\partial \omega}(\omega; p_L, p_m, K) P(d\omega|K) > \int_{\omega_1}^{\omega_2} 0 P(d\omega|K) = 0$$

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 mark-ups 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

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

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 $\eta = -\infty$.

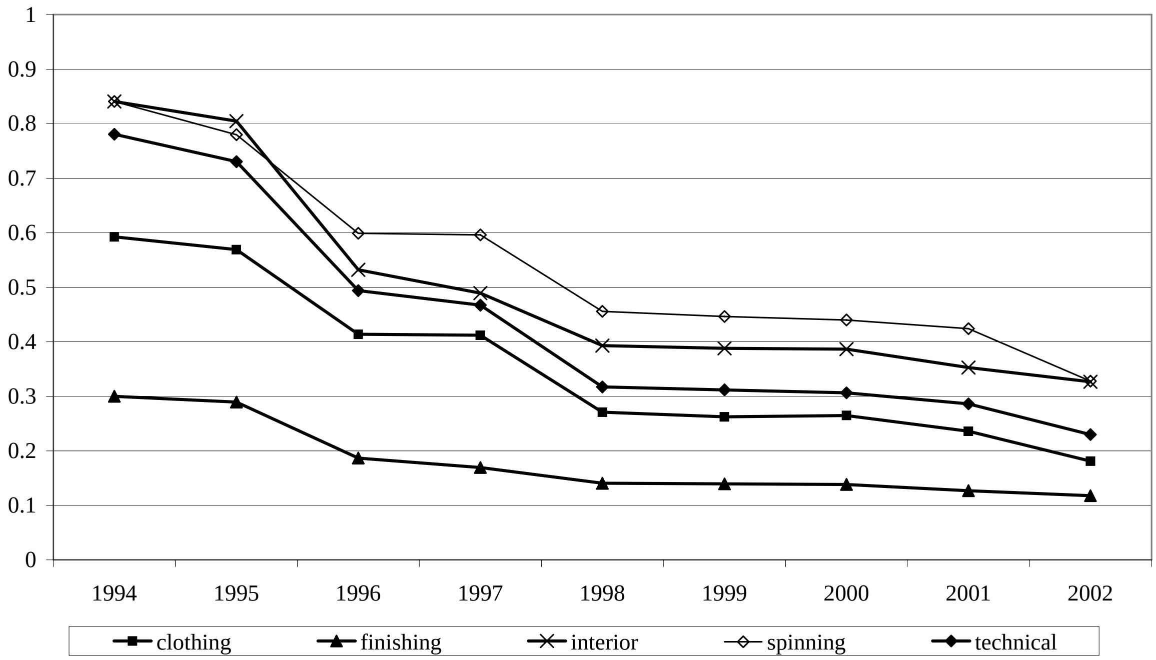

Figure 1: Evolution of Quota Protection Measure (qr) by Segment (1994-2002)

References

[1] Ackerberg, D,.Caves, K and Frazer, G. (2004). "Structural Estimation of Production Functions", U.C.L.A. mimeo

[2] Ackerberg, D, Benkard, L., Berry, S. and Pakes, A. (2005). "Econometric Tools for Analyzing Market Outcomes", Paper prepared for *Handbook of Econometrics*, J.J. Heckman (ed.)

[3] Ackerberg, D. and Pakes, A. (2005). "Notes on Relaxing the Scalar Unobservable Assumption in Olley and Pakes", mimeo, Harvard University.

[4] Arellano M. and Bond, S. (1991). "Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations", *Review of Economic Studies*, vol.58, 277-297.

[5] Bartelsman, E. J. and Doms, M. (2000). "Understanding Productivity. Lessons from Longitudinal Micro Data", *Journal of Economic Literature*

[6] Bernard, A.B., Redding, S. and Schott, P.K. (2003). "Product Choice and Product Switching", NBER WP 9789

[7] Berry, S. (1994). "Estimating Discrete-Choice Models of Product Differentiation", *Rand Journal of Economics*, 25(2), 242-262.

[8] Berry, S., Levinsohn, L. and Pakes, A. (1995). "Automobile Prices in Market Equilibrium", *Econometrica, 63, 841-890.*

[9] Buettner, T. (2004). "R&D and the Dynamics of Productivity", mimeo, London School of Economics.

[10] Collard-Wexler, A. (2006). Productivity Dispersion and Plant Selection in the Ready-Mix Concrete Industry, mimeo, New York University.

[11] De Loecker, J. (2004). "Do Exports Generate Higher Productivity? Evidence from Slovenia", LICOS DP 151.

[12] Dunne, T. and Roberts, M.J. (1992). "Costs, Demand and Imperfect Competition as Determinants of Plant-Level Output Prices", DP CES 92-5, Center for Economic Studies, US Bureau of the Census.

[13] Eslava, M., Haltiwanger, J., Kugler, A. and Kugler, M. (2004). "The Effects of Structural Reforms on Productivity and Profitability Enhancing Reallocation: Evidence from Colombia", CEPR DP 4569.

[14] Ericson, R. and Pakes, A. (1995). "Markov Perfect Industry Dynamics: A Framework for Empirical Work", *Review of Economic Studies*, Vol 62 (1), 53-82

[15] European Commission. (2005), website, http://europa.eu.int/comm/enlargement/pas/.

[16] Febeltex. (2003)."Anual Report 2002-2003 FEBELTEX", Belgium.

[17] Foster L., Haltiwanger, J. and Syverson, C. (2005). "Reallocation, Firm Turnover and Efficiency: Selection on Productivity or Profitability?", University of Chicago mimeo.

[18] Hall, R.E. (1988)."The Relation between Price and Marginal Cost in US Industry", *Journal of Political Economy*, 96 (5), 921-947.

[19] Harrison, A.E. (1994). "Productivity, Imperfect Competition and Trade Reform: Theory and Evidence, *Journal of International Economics*, 36, 53-73.

[20] Jaumandreu, J. and Mairesse, J. (2004). "Using price and demand information to identify production functions", mimeo.

[21] Katayama, H., Lu, S. and Tybout, J. (2003). "Why Plant-Level Productivity Studies are Often Misleading, and an Alternative Approach to Inference, NBER WP.

[22] Klette, T.J. and Griliches, Z (1996). "The Inconsistency of Common Scale Estimators When Output Prices are Unobserved and Endogenous", *Journal of Applied Econometrics*, vol 11 (4), 343-361.

[23] Konings, J., Van Cayseele P. and Warzynski, F. (2001). "The Dynamics of Industrial Mark-Ups in Two Small Open Economies; Does National Competition Policy Matters?", *International Journal of Industrial Organization*, 19, 841-859.

[24] Konings, J. and Vandenbussche, H. (2005). "Antidumping Protection and Markups of Domestic Firms", *Journal of International Economics*, vol. 65 (1), 151 - 165.

[25] Levinsohn, J. and Melitz, M. (2002). "Productivity in a Differentiated Products Market Equilibrium", Harvard mimeo.

[26] Levinsohn, J. and Petrin, A. (2000). "Estimating Production Functions Using Inputs to Control for Unobservables"., NBER WP 7819.

[27] Levinsohn, J. and Petrin, A. (2003). "Estimating Production Functions Using Inputs to Control for Unobservables"., *Review of Economic Studies*, Vol. 70, pp. 317-342.

[28] Melitz, M. (2001). "Estimating Firm-Level Productivity in Differentiated Product Industries", Harvard mimeo.

[29] Muendler, M.A. (2004). "Estimating Production Functions When Productivity Change is Endogenous", UCSD WP 05.

[30] Olley, S. and Pakes, A. (1996). "The Dynamics of Productivity in the Telecommunications Equipment Industry", *Econometrica*, Vol 64 (6), 1263-98.

[31] Pakes, A. (1994), "The Estimation of Dynamic Structural Models: Problems and Prospects", Part II. Mixed Continuous-Discrete Control Models and Market Interactions, Chapter 5, pp. 171-259, of Advances in Econometrics: Proceedings of the 6th World Congress of the Econometric Society, edited by J.J. Laffont and C. Sims.

[32] Pavcnik, N. (2002). "Trade Liberalization, Exit, and Productivity Improvement: Evidence from Chilean Plants", *Review of Economic Studies*, 69 (1), 245-76

[33] Petropoulos, W. (2000).."Productivity in an industry with differentiated products", University of Michigan, mimeo.

[34] Roeger, W. (1995). "Can Imperfect Competition Explain the Difference between Primal and Dual Productivity Measures? Estimates for US Manufacturing", *Journal of Political Economy*, 103 (2), 316-330.

[35] Smarzynska, B. (2004). "Does Foreign Direct Investment Increase the Productivity of Domestic Firms? In Search of Spillovers Through Backward Linkages", *American Economic Review, 94 (3), 605-627.*

[36] Syverson, C. (2004). "Market Structure and Productivity: A Concrete Example.", *Journal of Political Economy*, 112 (6), 1181-1222.

[37] Tybout, J. (2000). "Manufacturing Firms in Developing Countries", *Journal of Economic Literature*, Vol March, 11-44.

[38] Van Biesebroeck, J. (2006). "Exporting Raises Productivity in the Sub-Saharan African Manufacturing", *Journal of International Economics*, forthcoming.