Disentangling demand and productivity shocks using firm-level data from Pakistan

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Abstract

We address the two main types of bias that exist in the literature on firm-level productivity, i.e. input simultaneity and omitted price bias, by taking advantage of a unique firm-level dataset from Pakistan that contains disaggregated prices and output data, not only at the firm level but at the product level. Even though simultaneity bias has been addressed in the literature, this data allows us to also control for the omitted prices, rather than relying on sectoral deflators. Thus this disaggregated data allows us to estimate the actual productivity as opposed to measured productivity. We then compare our productivity results to those of De Loecker (2011) who controlled for unobserved prices and demand shocks by relying on demand shifters and exogenous trade protection measures in order to address both of the main estimation problems encountered when using aggregated firm revenue data. Our results indicate that the accuracy of the results from the De Loecker methodology is extremely dependent on the efficiency of the deflators used. Our results for Pakistan suggest that after we correct for both types of bias, the impact of a 10% reduction in tariffs on firm productivity falls from 3.33% to 0.2%. Also, our results show that any estimation of policy impacts on productivity that fails to incorporate demand shocks are significantly biased. Our results for Pakistan show that when demand shocks are incorporated into the analysis of tariff reduction on firm productivity, the impact is halved. The net impact of the Free Trade Agreement with China on firm’s physical productivity in Pakistan has been merely 2%, with the biggest gain being in the least protected segment.

Keywords: Firms, Trade, Productivity

JEL Codes: F14, L11, L23

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I. Introduction

Given the importance of productivity for economic growth, a wide range of literature focuses on the impact of various policy measures on productivity. In recent times, with the increased availability of micro data, much focus has been productivity at the firm level and one important area of attention is on how firm level productivity has been affected by increased openness to trade.

The trade-productivity linkage is well documented. Yu (2011) examines the impact of output tariff reductions on Chinese firms. His results conclude that tariff reductions enhances firm’s productivity via competition. Further, opening up leads to improvement in export quality which can then have spill-over effects. Ackah, et al. (2012) reach a similar conclusion. They examine the impact of trade liberalization on firm’s productivity in Ghana. They find a strong negative impact of nominal tariffs on productivity indicating that higher tariffs are distortionary for productivity. Bernard, Redding, & Schott (2011) reason that opening up to trade enhances productivity growth both within and across firms, forcing the least productive firms to exit the market since they cannot compete, raising the overall productivity.

Moreover, trade integration between countries leads to more revenue generation for firms, which may ultimately induce exporters to upgrade technology. Bustos (2011) concludes that firms in Brazil which face the largest tariff reduction increase investment in technology faster, with the effect being the strongest on the firms in the upper-middle part of the distribution. Bloom, Draca, & Reenen (2016) look at the impact of Chinese imports in the European market for a period of 1996-2007. They show that Chinese imports have led towards a 15% increase in technical intensity, contributing towards the upgradation of European technology over the past years.

This study aims to explore this trade-productivity linkage. In addition to this, we focus on how the estimates of the impact of trade liberalization on productivity can vary depending on how productivity is measured. Specifically, we argue that the measurement errors in estimating productivity, mainly due to the limited availability of disaggregated micro data, can lead to incorrect estimates. We are able to do this by using a unique micro firm-level dataset which allows us to compute accurate measures of productivity and then compare the trade-productivity estimates using our data with those using the more commonly available aggregated data.

In much of the literature on productivity, measurement issues in the estimation of productivity have mainly been because of the lack of disaggregated micro data. Though more detailed data has been made available over time, still much of the firm level data available is limited in two main ways. Firstly, most of the censuses done only report firm level revenues rather than disaggregated output and price data. Secondly, even the
revenue data that is available is aggregated at the firm level rather than at the product level.

A common practice in the literature is to then use deflated output as a proxy for actual output in order to compute productivity. This approach mainly relies on using sectoral deflators. Using sectoral deflators has two main limitations; firstly, it leads to omitted price bias and secondly, it will generate productivity estimates that contain price and demand variations.

While the input simultaneity bias is addressed in literature mainly by the work done on productivity by Olley and Pakes (1996) and Levinsohn and Pertrin (2003), what remains unaddressed is the omitted price bias which cannot be accounted for until actual disintegrated price-output data is made available. This leads to measurement issues in productivity, where measured productivity will be different than the actual productivity, potentially introducing inaccuracies in the estimation of the trade-productivity linkage.

The reliability of results using these sectoral deflators has remained controversial, despite being widely used in literature. Using sectoral price deflators might give different answers as compared to individual deflators (actual prices). Omitting individual prices can lead to measurement errors particularly if the real output is correlated with the prices (Abbott, 1991). Klette & Griliches (1996) argue that using deflated output as a proxy for actual output across firms can lead to biased results, particularly when the firms operate in an imperfectly competitive environment in which the prices are different across firms. Moreover, according to De Loecker (2011), using sectoral deflators will introduce a price bias, if the actual price of the firm is correlated with the firm’s input choices. The price error in this case will capture the difference between the industry price index and the firm’s prices, which is correlated with the firm’s input decision.

Besides the sectoral deflator being flawed, observing prices is itself important in order to control for demand shocks while estimating productivity in order to get the actual productivity estimates. According to Pozzi & Schivardi (2016) modern theories assume that firms are heterogeneous only along one side of unobserved dimension i.e. productivity. However, other dimensions, in particular, demand matters too. Differences in brand image, marketing, word of mouth and customer relations all develop heterogeneity amongst firms via the demand side. Literature has ignored this part, since to separately identify the demand and supply shocks, one needs to have information on actual prices.

Given the data limitations, much of the literature in this context does not separate out the demand effects and thus, relies on productivity estimates that contains the effect of prices and demand variations. According to Foster, Haltiwanger, & Syverson (2008) prices might reflect something other than productivity. If prices reflect market demand, then the common connection of productivity and growth might be overestimated and the impact of demand side factors that matter for growth might be understated.
This paper contributes to the literature on trade-productivity linkage by correcting for both input simultaneity bias and the omitted price bias, along with controlling for actual demand shocks estimated at the product level for each firm. To the best of our knowledge this study is the first one to do this in literature, using a detailed and disaggregated dataset, hardly available for other countries.

We use a panel of the Census of Manufacturing Industries (CMI) for Punjab, Pakistan for the years 2000, 2005 and 2010, where we observe disaggregated price and output data, not only at the firm level but at the product level. Hence, we have firm, product and time variation in our data set. Taking advantage of this data set, we control for the biases and demand shocks and recover the actual productivity estimates, which are then used to study the trade-productivity linkage.

We do this by examining the Free Trade Agreement (FTA) between Pakistan and China in 2006, under which there were significant tariff reductions by both the countries. In this study we focus specifically on the productivity effects of the FTA on the textile industry in Punjab, Pakistan.

This paper builds on the work done by De Loecker (2011) who studies this trade-productivity linkage for Belgium firms. He develops a unique methodology to estimate productivity controlling for demand shocks, while still relying on the typically available, aggregated firm-level revenue data. His work shows that after taking into account demand shocks and unobserved prices, trade liberalization leads to a 2 percent gain in productivity as compared to 8 percent as in the standard productivity measure used by most of the literature available in this context. De Locker goes further by saying “My results beg for a serious reevaluation of a long list of empirical studies that document productivity responses to major industry shocks and in particular, opening up to trade. My findings imply the need to study changes in the operating environment on productivity together with market power and prices in one integrated framework” (page 1407).

While De Locker (2011) develops a methodology to control for demand shocks, he does not observe physical output and prices. De Loecker jointly introduces the demand system into the production function and hence attempts to isolate the impact of trade liberalization on productivity from price and demand effects by relying on quota protection data to serve as exogenous demand shocks. He does this by introducing demand shifters, product and group controls and exogenous trade policy changes. However, his analysis still relies on revenue data and sectoral deflators. Though he incorporates demand into the system and tries to control for unobserved prices he does however acknowledge the fact that “using revenue data maybe a poor measure of true efficiency, we don’t know how important it is in practice” (page 1408).

1 We mainly focus on the textile sector since this is the major exporting sector of Pakistan. However, this exercise can be extended to other sectors as well.
This paper builds on De Loecker’s work in two ways. First, we address his data limitations by using disaggregated price and output data at the product level rather than relying on deflated output to estimate productivity. As mentioned earlier, this allows us to control for the omitted price bias along with the input simultaneity bias. Our data gives us the advantage to estimate actual demand shocks at the product level, which can then be aggregated at the firm level in contrast to De Loecker’s indirect method of controlling for demand shocks. Second, our data has an additional advantage over the data used by De Loecker. While De Loecker only observes the product mix for one year and assumes it to be the same for all years considered in his analysis i.e. from 1994 to 2002, we, however, observe the product mix of each firm for each year, and hence allow the product mix to change over time, adding more (and more accurate) variation to our analysis.

Using the actual price-output data, this study uses tariff rates as exogenous shifters to identify the actual demand shocks at the product level which are then aggregated at the firm level. This study develops an identification strategy to isolate the productivity response to trade liberalization from actual demand responses along with controlling for both the input simultaneity bias and omitted price bias by using actual output and price data rather than relying on sectoral deflators. This gives us estimates of actual productivity i.e. net of price and demand shocks. We then look at the impact of trade liberalization on our productivity estimates.

We then compare the results under De Loecker’s method using aggregated data to our results using disaggregated data. We aim to understand the extent to which this missing disaggregated data in the productivity literature can bias the productivity results and the extent to which De Loecker’s attempt to control for unobserved prices by accounting for demand shocks while relying on sectoral deflators helps solve this problem.

Our results indicate that only controlling for the input simultaneity bias and not for the omitted prices leads to biased results. We cannot properly control for the omitted prices until and unless we observe disaggregated price-output data. Moreover, it is also essential to control for demand shocks. In this context, De Loecker’s method works well in the absence of disaggregated data but is still very sensitive to the accuracy of the sectoral deflator used, since the deflator doesn’t take into account the price variation both within and across firms. Using disaggregated data, controlling for both the biases along with the demand shocks reports the overall elasticity of the textile sector to be -5.55, with clothing and interior being the most elastic segments. It is interesting to note that these segments are also the most highly protected segments. Comparing our results of a 10% reduction in tariff rate on firm’s productivity, the magnitude drops from 3.35% to 0.2% as we move on from ignoring all biases or demand shocks to controlling for all biases in the most accurate way. Moreover, only observing actual prices is not enough, we still need to incorporate the demand shocks. Even within De Loecker’s method, while still relying on
deflated output, incorporating the demand shocks reduces the impact of tariffs on firm’s productivity by half.

Overall, in terms of the total impact that tariff reductions under the FTA have had on productivity is 5% under De Loecker’s methodology as compared to 32% under biased estimates. However, when we use disaggregated data and compute the demand shocks in the most precise manner, the impact falls to 2%. Interestingly, while the overall impact on productivity has been low, the largest impact on productivity improvement has been for the spinning segment, which is the least protected segment. Complete elimination of tariffs has increased physical productivity by 16% in the spinning segment.

The rest of the paper is organized as follows. Section II describes the common types of biases found in the literature on productivity. Section III describes De Loecker’s methodology to estimate productivity. Section IV describes the estimation of productivity using actual disintegrated price and output data. Section V describes the Free Trade Agreement and the data sources. Main results are given in section VI while section VII concludes.

II. Common types of biases in the Productivity Literature

   i. Input Simultaneity bias

The issue of input simultaneity bias in the estimation of the production function dates back to the works of Marschak & Andrews (1944) who argue that researchers cannot measure the effect of changes in firm’s inputs on its output in the same way as a firm can, since these inputs are chosen by firms and not by the economists. Put in simple terms, if two firms use identical inputs, their output will not be the same for reasons not fully understood by the researcher. This unidentified or unobserved factor to which each firm is exposed to is mainly the firm’s own unique productivity, which known to the firm, but unknown to the researcher. The researcher only takes the values of inputs as given but does not fully understand the mechanism behind it.

A firm’s decision regarding the usage of input quantities and whether or not to liquidate depend on the firm’s own productivity. Hence this will generate a problem of simultaneity and selection bias. The problem of endogeneity occurs because the input choices of the firm are to a certain extent determined by the firm’s beliefs of its own productivity when put in use. If this is true, then there will be serial correlation between productivity and input choice in time period $t$. As a result the OLS will fail to take this into account leading to an upward bias in the input coefficients (Olley & Pakes, 1996).

One possibility to address this bias is to estimate the exact input demand conditions for the firms, but that of course is cumbersome and requires a wide
range of assumptions given that input usage data is typically available at firm level rather than at product level in literature. Another way could be to consider productivity as time invariant and use a within estimator. However, considering productivity to be fixed, especially for panel data, is quite restrictive (DeSouza, 2006). The other way around, as suggested by Blundell & Bond (2000), is differencing the variables and using lagged inputs as potential instruments. However, differencing variables means losing variation and instruments might only be weakly correlated with variables if they are differenced (Wooldridge, 2005).

To address the issue of the lack of good instruments and to deal with simultaneity bias, alternate methods have been developed. The two most popular and commonly used methods are the ones by Olley & Pakes (1996) and Levinsohn & Petrin (2003), abbreviated OP and LP hereafter. OP develop a semi-parametric productivity estimator where they use investment as a proxy for the firm’s productivity. They assume that there is only one state variable, which is the unobservable productivity which causes differences in firms’ behavior at a given point in time. Hence, using investment as a proxy for productivity can control for the inputs and unobserved productivity. Levinsohn & Petrin (2003) build on the works of Olley & Pakes and show that other than investment, the intermediate inputs (typically materials) can also be used to control for the correlation between inputs and productivity. They take the advantage of the time difference of hiring these inputs by firms². Both these methods are widely used in literature on productivity to correct for the simultaneity bias. We also rely on the LP method for its advantages to control for simultaneity bias in our study.

### ii. Omitted Price bias

Not observing output prices leads to omitted price bias, especially when relying on sectoral deflators.

To understand the omitted price bias, let’s start with a simple production function:

\[ Q_{it} = A_{it} K_{it}^{\alpha K} L_{it}^{\alpha L} M_{it}^{\alpha M} \]  

(1)

Where \( Q_{it} \) is the firm-level output, \( K_{it} \) is the firm-level capital, \( L_{it} \) is the firm-level labor and \( M_{it} \) is the firm-level raw materials. \( \alpha \)'s are the factor share and \( A_{it} \) is the firm level productivity. Taking logs we re-write the above equation as

\[ q_{it} = \beta_k k_{it} + \beta_l l_{it} + \beta_m m_{it} + a_{it} + u_{it} \]  

(2)

² Levinsohn & Petrin (2003) argue how their approach is better than using investment as a proxy for productivity. The obvious advantage is data driven, since the investment proxy only works for non-zero investment cases, where around half of the firms do report zero investment. Using materials instead, solves this problem, since firms always report positive values of materials or electricity. The other advantage being that firms might react to a productivity shock by adjusting their intermediate inputs more since they are easier and cheaper to update as compared to adjusting the investment demand function, which in that case then does not fully respond to productivity.
where the lower case indicates that the variable is in log. \( u_{it} \) is the unobserved error term. Since physical output is not observed in most of the datasets, the literature relies on deflating revenues to get deflated output instead of \( q_{it} \). The log of deflated revenue is given as:

\[
r_{it}^* = p_{it} + q_{it} - \overline{p}_{it}
\]  

(3)

where \( p_{it} \) is the log of sectoral deflator. Combining both the equations (2) and (3) gives us

\[
r_{it}^* = \beta_k k_{it} + \beta_l l_{it} + \beta_m m_{it} + (p_{it} - \overline{p}_{it}) + \Omega_{it} + u_{it}
\]

(4)

Given the data constraint in the literature where firm-level prices \( p_{it} \) are not available, we do not observe the term \( p_{it} - \overline{p}_{it} \) (the difference between firm-level and industry prices). This leads to an omitted price bias particularly if the firm’s inputs are correlated with this price difference, i.e. if:

\[
E(x_{it}(p_{it} - \overline{p}_{it})) \neq 0
\]

where \( x_{it} = (l_{it}, m_{it}, k_{it}) \)

Hence, there will be omitted price bias. True estimates of productivity therefore requires controlling for this price difference. The problem even becomes severe for multi-product firms since firms produce heterogeneous products and charging the same price even for all products within the same firm leads to biased results, let alone charging the same price across firms.

Secondly, besides the omitted price bias, not observing and controlling for prices means that the measured productivity estimates might not be the true ones since they might be incorporating demand variations, rather than reflecting the actual productivity. Incorporating the demand shocks into the analysis is important. Pozzi & Schivardi (2016) argue that even if actual output is observed, output prices are still needed to control for the demand shocks. Firms are not just heterogenous in productivity but also in how customers perceive the firm based on its image, visibility of product and brand name as a result of advertisement for example. Hence, there is a need to incorporate this demand heterogeneity into the analysis. Productivity and demand shock are different. Productivity shocks are represented by a shift in production technology where businesses might respond by reallocation, reorganizing, using different mix of inputs including capital, changing skill mix of employees etc. If firms miss out on implementing these complementary innovations due to lack of expertise, they miss out on taking the full advantage of the productivity shocks. This however, may not be true for demand shocks. Under a demand shock, the need to cater to a large body of customers can simply be met by scaling up the production without any need of changing the organizational working. In simple words, less capable firms, which lack to expertise to reorganize, may not be fully able to adjust to productivity shocks, but not necessarily towards the demand
shocks. Using data on Italian firms, they show that firms respond more to demand shocks then they do to productivity shocks.

Carlsson, et al. (2014) study the response of demand and productivity shocks towards firms adjustment in employment using data from Swedish firms. They conclude that firms respond more to demand shocks as opposed to productivity shocks. Their results show that demand shocks, especially those which are premenant in nature are the main driving force behind job and worker reallocation.

Foster, Haltiwanger, & Syverson (2008) study firm’s survival decision based on its productivity and demand shocks. Results indicate that firms are more likely to exit due to a low demand shocks rather than low productivity (3 to 4 times larger impact). Hence, while both factors matter, demand variations amongst producers is the dominant factor for survival and cannot be ignored. They argue the importance of incorporating demand into the analysis to back out “true productivity” estimates since prices might reflect something other than productivity. In most cases prices might be a reflection of market demand and as a result the link between productivity and growth might be overestimated and the impact of demand side factors that matter for growth might be understated. Controlling for demand shocks in hence essential in the measurement of productivity, which can not be done until prices are observed.

Given both the input simultaneity bias and omitted price bias in literature, studies do address the simultaneity bias by relying on the method developed by OP (1996) and LP (2003). Omitted price bias on the other hand remains unaddressed in literature, mainly because of the lack of individual product-level price and output data. As a result of this, relying on sectoral deflators introduces measurement errors in productivity. Since prices are not observed, demand shocks are also not controlled for, giving us productivity estimates which are different from the actual productivity estimates.

III. De Loecker’s (2011) Methodology

De Loecker (2011) studies the trade-productivity linkage by developing a unique methodology in which he controls for the omitted price bias and demand shocks along with the input simultaneity bias. He does this by incorporating a demand system into the analysis while still using the disaggregated firm level revenue data. Relying on observed demand shifters, product and group dummies along with exogenous trade policy changes, his methodology allows him to estimate elasticities which differ according to product segments. He then looks at the response of trade liberalization on productivity. His results indicate that trade liberation only lead to a 2% productivity gains for the Belgian textile firms when controlling for demand shocks as opposed to 8% gain under the standard measure of productivity.
**Single Product Firms**

De Loecker (2011) starts out with a simple model considering single product firms. He then incorporates multi-product and multi-segment firms into the analysis.

Consider a single product firm with a simple Cobb-Douglas production function:

\[ Q_{it} = K_{it}^{\alpha K} L_{it}^{\alpha L} M_{it}^{\alpha M} \exp(\omega_{it} + u_{it}) \]  

Where firm \( i \) produces output \( Q_{it} \) at time \( t \) using capital \( K_{it} \), labor \( L_{it} \) and materials \( M_{it} \). \( \alpha \)'s are the respective input shares. \( \omega_{it} \) are the firm-specific productivity shocks while \( u_{it} \) is the idiosyncratic error term.

Since the physical output \( Q_{it} \) is not observed due to lack of disintegrated data, he relies on sectoral deflators to back out deflated output. This has two main implications; firstly, it biases the input coefficients if the price difference is correlated with the input usage i.e. the omitted price bias and secondly, it also picks up demand variations which might introduce a relationship between trade and productivity simply due to demand and price variations. This then gives us *measured* productivity rather than *actual* productivity estimates.

To measure the response of actual productivity to trade liberalization, De Loecker introduces a demand system for firm \( i \). He considered a standard horizontal product differentiated demand system based on constant elasticity of substitution (CES), where he allows the elasticity of substitution to differ between different segments, subscripted \( s \).

\[ Q_{it} = Q_{st} \left( \frac{P_{it}}{P_{st}} \right)^{\eta_s} \exp(\xi_{it}) \]  

The demand system given in equation (6) indicates that the firm’s own demand depends upon the sectoral demand \( Q_{st} \), its own price \( P_{it} \), the average price in the industry \( P_{st} \) and an unobserved demand shock \( \xi_{it} \). \( \eta_s \) is the elasticity of substitution which varies according to the segments, \( s \). Producers within the textile sector then face different demand elasticities based upon the textile segment(s) they are active in. It is worth noting that \( Q_{st} \) over here includes the total demand for the textile products in each of the segments in the market.

Since a firm’s revenue is given as \( R_{it} = Q_{it} P_{it} \), combining this with the expression of price from equation (6) we get:

\[ R_{it} = Q_{it} \left( \frac{P_{st}}{P_{st}} \right)^{\eta_s} Q_{st}^{-1/\eta_s} P_{st} \exp(\xi_{it})^{-1/\eta_s} \]  

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3 This implies a segment specific Lerner Index.
4 This is one of De Loecker’s contribution in literature along with his unique methodology where he allows for elasticities to vary across segments while the common practice in literature is to have a single markup and elasticity (Klette & Griliches (1996); Levinshon & Melitz (2006)).
5 Refer to section V for a detailed discussion on the construction of \( Q_{st} \). It is import to include imports in this context.
Writing in log form we get the sales generating production function as follows:

\[ \hat{r}_{it} = \beta_l l_{it} + \beta_k k_{it} + \beta_m m_{it} + \beta_s q_{st} + \omega_{it}^{*} + \xi_{it}^{*} + u_{it} \]  

(8)

Where \( \hat{r}_{it} \) is the deflated revenue given as \( (r_{it} - p_{st}) \) where the lower case letters represent logs. Note that the coefficients over here are given as \( \beta \)'s as opposed to \( \alpha \)'s which are the reduced form parameters. The coefficient of interest over here \( \beta_h = \frac{(\eta_h + 1)}{\eta_s} \alpha_h \) where \( h = \{l, m, k\} \). For the segment specific demand parameter \( \beta_s = \frac{1}{|\eta_s|} \). The returns to scale \( \gamma \) are obtained by summing up the production parameters, i.e. \( \gamma = \alpha_l + \alpha_k + \alpha_m \). The unobserved productivity and demand parameters are given as \( \omega_{it}^{*} = \omega_{it} \left( \frac{\eta_s + 1}{\eta_s} \right) \) and \( \xi_{it}^{*} = \xi_{it} |\eta_s|^{-1} \).

**Multi-Product and Multi-Segment Firms**

The model above is further extended to allow for multi-product firms. The product-level information is then aggregated at the firm-level as an extra step. However, as with much of the data, the input usage is not observed at the product level but rather at the firm level. The standard assumption then in literature is then to assume that firms have identical production functions across products which is then aggregated at the firm level. This assumption requires the inputs to be used equally depending on the number of products being produced by the firm.6

Under this assumption, the production function of product \( j \) for firm \( i \) at time \( t \) is given as follows:

\[ Q_{ijt} = (c_{ijt} L_{it}^{\alpha_l}) (c_{ijt} K_{it}^{\alpha_k}) (c_{ijt} M_{it}^{\alpha_m}) \exp(\omega_{it} + u_{it}) \]  

(9)

\[ = J_{it}^{-\gamma} Q_{it} \]  

(10)

c_{ijt} over here is the share of product \( j \) in firm \( i \)'s total input usage at time \( t \). Equation (10) employs the concept that the inputs are evenly spread across all products in exactly the same proportion as the number of products i.e. \( c_{ijt} = J_{it}^{-\gamma} \). This means that the multiproduct framework only requires adding in the number of products produced to accommodate the multiproduct firms in the analysis.7 This incorporates the idea of proportionality of input usage.

Hence in order to incorporate multiproduct firms, we just need to control for the number of products being produced, where equation (8) can now be written as:

\[ \hat{r}_{it} = \beta_{np} np_{it} + \beta_l l_{it} + \beta_k k_{it} + \beta_m m_{it} + \beta_s q_{st} + \omega_{it}^{*} + \xi_{it}^{*} + u_{it} \]  

(11)

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7 This is done to incorporate the data restriction where input usage is not observed according to the products produced but is rather observed at the firm level.
Where $np_{it} = \ln (J_{it})$. For single product firms, $\ln (J_{it})=0$. Note the asterisk on unobservable is to keep the track of difference between actual productivity (demand) unobservable and the unobservable multiplied by the inverse of the demand parameters as mentioned earlier.

The model can be further expanded by allowing for multi-segment firms. For this, the demand of each segment $s$ in which the firm is active in needs to be incorporated. This is done by simply expanding the term $q_{st}$ to $\sum_{s=1}^{S} \beta_{s} s_{is} q_{st}$, where a dummy variable $s_{is}$ is there for each firm if its active in segment $s$. A firm can now face $S$ different demand conditions depending upon the number of segments its active in, which then helps identify segment specific elasticities. Hence, in order to incorporate multi segment firms, equation (11) can now be written as:

$$r_{it} = \beta_{np} np_{it} + \beta_{l} l_{it} + \beta_{k} k_{it} + \beta_{m} m_{it} + \sum_{s=1}^{S} \beta_{s} s_{is} q_{st} + \omega_{it}^{*} + \xi_{it}^{*} + u_{it}$$ (12)

We can now estimate equation (12) and use it on the entire sample. It accounts for single product firms, single segment – multi product firms and multi segment-product firms.

**Estimation Strategy**

Under the CES demand system, the unobserved prices are picked up by the variation in inputs and demand per segment as represented by $\sum_{s=1}^{S} \beta_{s} s_{is} q_{st}$. However, other factors may impact the prices and must be taken into account, else they will bias the coefficients. One potential candidate for this are the tariff rates. Differences in tariff rates across products and over time impact prices. Following Goldberg’s (1995) strategy, De Loecker decomposes the unobserved firm specific demand shocks ($\xi_{it}$) based on the nested structure of the product-level data into three observable components and an unobservable shock as shown by equation (13). The observable components are based on the products a firm produces, the sub-segments the firms is active in along with the firm specific tariff rate.

$$\xi_{it} = \xi_{j} + \xi_{g} + \tau Tariff_{it} + \widehat{\xi}_{it}^{*}$$ (13)

$j$ refers to the product and $g$ refers to the product group (sub segment), while $\tau$ is the the impact of tariffs on the demand shock.8 $\widehat{\xi}_{it}^{*}$ is the unobserved part in the demand shock (i.i.d). This decomposition of the demand shock ($\xi_{it}$) helps capture both the product group segment demand differences and the difference in the tariff rates. As the tariff rates vary by products and firms produce different products, the firm-level tariff rates vary and hence act as firm-specific residuals in the demand shock.

In terms of the data, we have the nested demand for products where they are nested by dividing them into segment $s$, under which we have sub-segments $g$ and within those we have products $j$. Refer to appendix A.

8 De Loecker (2011) uses quota restriction rather than tariffs as a source of international trade liberalization.
To illustrate this, $\xi_j$ is a set of product level dummies represented as $\sum_{j \in J(i)} \delta_j D_{ijt}$, while $\xi_g$ is a set of sub segment dummies represented as $\sum_{g \in G(i)} \delta_g D_{igt}$. Combining equation (12) and (13) we apply the data to the following equation (14):

$$\tilde{r}_{it} = \beta_{np} n_{it} + \beta_{l} l_{it} + \beta_{m} m_{it} + \sum_{s=1}^{S} \beta_{s} s_{it} q_{st} + \sum_{j \in J(i)} \delta_j D_{ijt} + \sum_{g \in G(i)} \delta_g D_{igt} + \tau_{r} Tariff_{it} + \omega_{it} + \epsilon_{it} \quad (14)$$

$D_{ijt}$ are a set of dummy variables for products taking a value of 1 if the firm $i$ produces a product $j$ and 0 otherwise at time $t$. Similarly, $D_{igt}$ is a set dummy variable for sub-segment $g$ taking a value of 1 if the firm is active in a sub-segment and 0 otherwise at time $t$. It is worth noting that we observe the product mix for firms for every year, hence our product and product-segment dummies for a firm vary over time. De Loecker observes this product mix for only one year and assumes that the product mix remains constant over time from 1994 to 2002. Hence, we have this data advantage over that utilized by De Loecker.\(^9\)

Equation (14) is then taken to the data. It is worth noting that now De Loecker has accounted for both the biases as mentioned in section II. The omitted price bias and the demand shocks are mainly controlled by De Loecker through (i) allowing for product and group effects by including the term $\sum_{j \in J(i)} \delta_j D_{ijt} + \sum_{g \in G(i)} \delta_g D_{igt}$, (ii) taking into account the fact the tariffs can impact demand and hence by controlling for tariffs by including the term $\tau_{r} Tariff_{it}$ and (iii) finally including the demand per segment faced by firms i.e. $\sum_{s=1}^{S} \beta_{s} s_{it} q_{st}$. The simultaneity bias is accounted for by using Olley and Pakes (1996) and Levinsohn and Petrin (2003) to proxy for unobserved productivity. The underlying assumption depends upon whether we rely on a static input (materials) or a dynamic input (investment) as a proxy for productivity.

The theory behind how the trade shocks impact the productivity process is mainly based on the X-inefficiency argument where lower tariffs increase competition and firms react to increased competition by eliminating inefficiencies, increasing the overall productivity mainly through reallocation. Therefore, De Loecker, in his methodology allows lagged tariffs to impact productivity. The idea behind lagged tariffs is that it takes time for firms to cut slack, hire new managers or introduce better practices which ultimately enhance productivity. Hence productivity depends upon lagged productivity and lagged tariffs as represented by equation (15). On the other hand, tariffs impact firm-level residual demand instantaneously (as shown in equation (13)) and create firm level variations in revenue.

$$\omega_{it}=g_{it} (\omega_{it-1}, Tariff_{it-1}) + v_{it} \quad (15)$$

\(^9\) Refer to page 19 for a detailed discussion on how the product mix varies over time in our data set.
The main assumption over here is that the tariff rates are completely exogenous and hence, any shocks to productivity \( v_{it} \) are uncorrelated with current (\( tariff_{it} \)) or lagged tariffs (\( tariff_{it-1} \)) which is important for the identification strategy. This is mainly because no individual firm has the power to influence or set the tariff rates.

While De Loecker uses both OP (1996) and LP (2003) to correct for input simultaneity bias, we present the results for the LP approach here. The main advantage being that we can use materials as a proxy for productivity for which all firms report positive values for all years rather than relying on the investment data.

The choice of materials \( m_{it} \) for a firm is directly related to firm’s productivity, capital stock as well as all the demand variables including tariff rates, segment dummies and product and group dummies.

\[
m_{it} = m_t(k_{it}, \omega_{it}, tariff_{it}, q_{st}, D_{it}) \tag{16}
\]

Where \( D_{it} \) over here represents all the product and group dummies\(^{10}\). Using function \( h(.) \) to proxy for productivity we get

\[
\omega_{it} = h_t(k_{it}, m_{it}, tariff_{it}, q_{st}, D_{it}) \tag{17}
\]

Hence we estimate

\[
\tilde{r}_{it} = \varphi_t(k_{it}, m_{it}, tariff_{it}, q_{st}, D_{it}) \epsilon_{it} \tag{18}
\]

Where \( \varphi_t = \beta_k k_{it} + \beta_m m_{it} + \beta_s q_{st} + + \delta D_{it} + \tau Tariff_{it} + h_t(.) \).

The coefficient for labor is obtained in the first stage. The other parameters of interest are obtained in the second stage using the generalized methods of moments (GMM) with the following moment conditions

\[
E \left\{ v_{it+1} (\beta_m, \beta_k, \beta_s, \tau, \delta) \begin{pmatrix} m_{it} \\ k_{it+1} \\ q_{st} \\ tariff_{it+1} \\ D_{it} \end{pmatrix} \right\} = 0 \tag{18}
\]

The coefficient \( \tau \) is identified by the moment condition \( E(tariff_{it+1} v_{it+1}) = 0 \) implying the exogeneity of the tariff rates. The parameters \( \beta_s \) are identified by the condition that \( v_{it+1} \) i.e. shocks to productivity are not correlated with the lagged total (segment) output i.e. \( E(q_{st} v_{it+1}) = 0 \). Materials and capital are identified by the standard moment conditions in

\(^{10}\) As mentioned above, we allow the product and group dummies to vary with time since we observe the product mix for each firm for each year. This is the added advantage we have over De Loecker’s data where he just observes the product mix for one year and assumes it to be fixed over time.
literature\textsuperscript{11}. The main idea behind the results is that tariffs in this model affect productivity with a lag but affect the prices through the residual demand instantaneously.

Productivity can then be computed using the estimated parameters from the GMM analysis above and can be given as

$$\hat{\omega}_{it} = (r_{it} - \beta_l l_{it} - \beta_m m_{it} - \beta_k k_{it} - \beta_s q_{st} - \delta_t D_{it} - \tau T tariff_{it}) \left( \frac{\eta_s}{\eta_s + 1} \right)$$ \hspace{1cm} (19)

It is worth noting that the productivity is rescaled given the difference between $\omega_{it}$ and $\omega^*_{it}$ mentioned in the text earlier. Productivity measures both with and without product and group dummies are considered to evaluate the role of controlling for demand shocks in the analysis.

It is worth noting that these estimates of productivity account for both the input simultaneity bias and omitted price bias along with the demand shocks.

Finally, once the estimates of productivity are obtained using equation (19), we then look at the impact of tariffs on the productivity as shown by equation (20) on firm-level productivity.

$$\tilde{\omega}_{it} = \chi_0 + \chi_1 T ariff_{it} + e_{it}$$ \hspace{1cm} (20)

IV. Estimating actual product specific demand shocks using disaggregated price and output data

Taking advantage of the disaggregated price and output data at the product level for each firm in our sample, we compute the demand shock faced by each firm $i$ at the product level $j$. While De Loecker’s decomposition of the demand shock is given by equation (13) where he decomposes the demand shock $\xi_{it}$ into three observable components namely the product dummies, product-group (sub-segment) dummies and the tariff rate at the firm level, we take a different approach. We compute the actual demand shocks at the product level first and then aggregate them at the firm level. We do this by estimating the demand equation for each firm $i$ at the product level, using actual product-wise output and price information. We enjoy the benefit of having a rich data set which gives us this detailed information, not only at the firm level but at the product level\textsuperscript{12}.

We compute the following demand equation for product $j$ by firm $i$ at time $t$:

$$q_{jit} = \gamma_0 + \gamma_1 p_{jit} + \xi_{jit}$$ \hspace{1cm} (21)

\textsuperscript{11} Interaction terms with D are not included for practical implementations in the estimation of GMM. However quadratic terms of inputs and input interactions are included in the estimation of $\phi$.

\textsuperscript{12} Refer to section V for a detailed discussion on the data set used.
Where \( q_{ijt} \) and \( p_{jit} \) is the quantity of product and price of product \( j \) produced by firm \( i \) at time \( t \). The residual \( \xi_{jit} \) is the demand shock at the product level \( j \) faced by firm \( i \) at time \( t \).

Taking equation (21) directly to the data is problematic since there might be a simultaneity bias as observed in a typical demand model like this. To cater for this we instrument for prices. Since we observe the tariff rates at the product level for all the years, we use tariff rates as an instrument for prices. The main exogeneity argument being that tariffs can impact the prices charged by firms mainly due to more competition from the world but one firm itself has no ability to influence the tariff rates. Hence we instrument for prices using tariff rates as shown by equation (22).

\[
p_{jit} = \theta_0 + \theta_1 \text{tariff}_{jt} + e_{jit} \tag{22}
\]

Where \( \text{tariff}_{jt} \) is the tariff rate observed for each product \( j \) for time period \( t \). \( e_{jit} \) is the idiosyncratic error term.

We then estimate the second stage as:

\[
q_{jit} = \gamma_0 + \gamma_1 \hat{p}_{jit} + \xi_{jit} \tag{23}
\]

The residuals obtained from equation (23) can then be summed up at the firm level based on the revenue share \( s_{jit} \) of product \( j \) produced by firm \( i \) at time \( t \).

\[
\xi_{it} = \sum s_{jit} \xi_{jit} \tag{24}
\]

Once we have estimated these demand shocks, we can directly control for them instead of relying on the product and product group dummies \( D_{it} \) as under De Loecker’s methodology. Hence equation (16) can be rewritten as

\[
m_{it} = m_t(k_{it}, \omega_{it}, \text{tariff}_{it}, q_{st}, \xi_{it}) \tag{25}
\]

since we now directly have estimates for \( \xi_{it} \). It is worth noting that now rather than controlling for a bunch of dummies (product and product group) we just control for one variable i.e. \( \xi_{it} \) since we obtain the estimates of it from equation (24).

The moment conditions then become

\[
E \left\{ v_{it+1} (\beta_m, \beta_k, \beta_s, \tau, \delta) \left( \begin{array}{c} m_{it} \\ k_{it+1} \\ q_{st} \\ \text{tariff}_{it+1} \\ \xi_{it+1} \end{array} \right) \right\} = 0 \tag{26}
\]

With the parameters obtained by GMM, we estimate productivity using equation (19) and finally estimate the impact of tariffs on productivity as in equation (20). This will be the actual productivity parameter since this is measured using actual output, prices and demand shocks.
V. Background of the Free Trade Agreement (FTA) between China and Pakistan and the Data Sources

Free Trade Agreement between China and Pakistan

Pakistan and China signed a Free Trade Agreement (FTA) in 2006 under which tariff rates were decreased on both the sides, facilitating cross border movements by establishing bilateral corporation between both the countries. The first phase of the FTA aimed to cover the first five years of the agreement. Negotiations for the second phase began in 2013, with both the parties inclined on reducing tariffs on no less than around 90% of the products\textsuperscript{13}. As a result, the total trade between both the countries rapidly increased from US$ 3.5 billion in 2006 to US$ 14.3 billion in 2013 with China being the second largest importing partner of Pakistan, having a share of 16.17% in of Pakistan’s total imports as of 2013 (Xin, et al., 2014).

Figure 1 below shows the trade flows between both the countries. Clearly, Pakistan’s imports from China rose at a faster rate than its exports to China, showing a marked difference between the trades balances between both the countries, where Pakistan imports three times as much than its exports to China. In other words, China is making its way into Pakistan at a much faster pace than Pakistan is into China, especially after the development of the China-Pakistan Economic Corridor (CPEC) route (Irshad & Xin, 2015).

Chaudhry, et al. (2017) examined the performance of sectors in Pakistan that were given more access to Chinese markets by means of tariff reductions (the vulnerable sectors) as opposed to the sectors for which the tariff rates remained roughly the same. They conclude that in these sectors, Pakistan increased its imports from China, while productivity, value added and value added per worker fell. They also examine the performance of sectors in which Pakistan gained more access in the Chinese market. They show that although Pakistan’s export and employment in these sectors has gone up, productivity and value added has gone down. This indicates a dire need on the side of Pakistan to carefully analyze the clauses of the FTA with China.

\textsuperscript{13} Detailed FTA report regarding the textile sector are available at: https://rdacell.com/Documents/Pakistan-ChinaFree.pdf
Data Sources

i. Census of Manufacturing Industries (CMI) Punjab, Pakistan: Firm- and Product-level data

The CMI is a firm-level census conducted every 5 years. It is a well-detailed survey containing information regarding the firm level revenues, input quantities and prices along with information on employment, various capital stock measures, material inputs, investment etc. Using the CMI wave of 2000, 2005 and 2010, we construct a panel dataset focusing specifically on the province of Punjab in Pakistan.

What gives this data set edge over various other data sets in micro literature is that the sales and revenue information is not only available at the firm level, but is also available at the product level. That means for every firm we observe its product mix for each of these years and also the output and prices for each product it produces. This is one advantage we have not only over De Loecker’s data set but over most of the microdata sets available in literature. Observing disaggregate price and output data not only at the firm level but at the product level, helps us eliminate the problem of omitted price bias and measurement issues that arise due to relying on the sectoral deflator. Observing actual prices will help us completely eliminate such errors giving us the actual productivity measure. This data set is itself a contribution in micro literature.

In our analysis, we specifically focus on the textile sector. Table 1 below shows the distribution of the textile firms according to the CMI used in our analysis.
Table 1: Distribution (Number) of the Textile Firms

<table>
<thead>
<tr>
<th>Year 2000, 2005 and 2010</th>
<th>Year 2000 and 2005</th>
<th>Year 2000 and 2010</th>
<th>Year 2005 and 2010</th>
<th>Year 2000 only</th>
<th>Year 2005 only</th>
<th>Year 2010 only</th>
</tr>
</thead>
<tbody>
<tr>
<td>95</td>
<td>100</td>
<td>40</td>
<td>83</td>
<td>358</td>
<td>265</td>
<td>303</td>
</tr>
</tbody>
</table>

The products available in the CMI data were coded using the Pakistan Standard Industrial Classification (PSIC) codes which are based on International Standard Industrial Classifications (ISIC) codes. We first convert these PSIC codes into relatable ISIC codes after which we link them into convertible Harmonized System (HS) codes using the conversion codes made available by the United Nations International Trade Statistics. We convert them to make them comparable with the international data bases which mainly rely on HS product coding\(^\text{14}\).

Following De Loecker's classification within the textile sector, we take the textile sector as a sector, where we divide the textile firms into five different segments; (i) finishing (ii) spinning (iii) interior (iv) clothing and (v) technical\(^\text{15}\). Within each of these segments, we have product groups (sub-segments) and then finally within those product groups we have the products.\(^\text{16}\)

Besides observing disaggregated data at the product level, our data set has an additional advantage as compared to De Loecker's data set. De Loecker only observes the product mix for one year and assumes that the product mix remains constant for the firm from 1994-2002. This study builds on De Loecker's limitation by allowing for the product mix of firms to vary with time. Assuming that the product mix remains the same for around a decade is a strong assumption to make. Bernard, et al., (2011) show that the firms in the United States do indulge in product switching over time and hence change their product mix.

Assuming the firms produce the same product over a span of 10 years means that the distribution of firms across segments remains constant. Table 2 shows the composition of firms in different segments within the textile sector for the year 2000, 2005 and 2010. Clearly over the span of ten years, the distribution of firms across segments has changed considerably. For example, in 2000 only around 3% of the firms were active in the interior segment, while at the end of 2010, more than 20% of the firms are active within the interior segment. Similarly, while less than 10% of the firms were active in the finishing segment in 2000 but by the end of 2010, this number increases to more than 25%. Hence

\(^{14}\) We also convert them into relatable HS codes since we have to link these products with their respectable tariff rates which are available by the World Trade Organization (WTO) based on HS coding system.

\(^{15}\) See appendix A for a broader classification of these segments.

\(^{16}\) De Loecker uses the classification as made available by FEBELTEX (2003) reports which is an organization of the Belgian Textile Industry. They themselves list classify the textile sector into five segments and product segments based on various product categories (www.febeltex.be).
assuming that the products produced and hence, the segments the firms have been active in is constant is a strong assumption to make.

<table>
<thead>
<tr>
<th>Table 2: Segment Wise composition of firms (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
</tr>
<tr>
<td>Spinning</td>
</tr>
<tr>
<td>Clothing</td>
</tr>
<tr>
<td>Interior</td>
</tr>
<tr>
<td>Technical</td>
</tr>
<tr>
<td>Finishing</td>
</tr>
</tbody>
</table>

Besides these segment dynamics changing, if we further look at the at the textile sector, we see that the nature of firms has changed. Table 3 shows the proportion of multi-segment and multi-product firms\(^7\) and the average number of differentiated products produced by firms within one product category\(^8\). According to this table, we can see that in the year 2000, many of the firms were single-segment, single product firms with a lot of focus on product differentiation. In other words, the firms were focused on producing different varieties of the same product falling under the same HS product category, with an average firm producing around 8 different varieties of the same product. This goes to a maximum of 22 varieties produced by one firm in the data set. In 2005, we can see that the firms change their focus from producing differentiated products to rather being a multi-product firm. While the average variety of differentiated product produced falls to 4, we see firms moving towards different products rather than producing different varieties of the same product. More than 20% of the firms reported in 2005 are multi-product firms. Finally, in 2010, we see the firms focusing more on being a multi-segment firm, diversifying their segments rather than a focus on diversifying products or differentiating them. This further builds on table 2, were we see a more balanced distribution of firms across segments as firms now focus on being multi-segment firms in 2010.

<table>
<thead>
<tr>
<th>Table 3: Percentage of Multi-Segment and Multi-Product Firms along with the average number of differentiated products produced</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
</tr>
<tr>
<td>Multi-Segment firms</td>
</tr>
<tr>
<td>Multi-Product firms</td>
</tr>
<tr>
<td>Average number of differentiated products produced by firms</td>
</tr>
</tbody>
</table>

We can clearly see that the firm dynamics have changed over time. Hence, it is important to observe the product mix for firms at each of the time period. Keeping the product mix

---

\(^7\) Firms can be multi-product within the same segment (multi-product, single segment firm) or because of producing in other segments (multi-product, multi-segment firm).

\(^8\) We define differentiated products as producing multiple varieties of the same product, having the same HS code.
the same will not only give us a wrong estimate of the number of products produced \((n_p_{it} - n_p_i)\) as the error) but will not allow us to take the changing firm dynamics over time into account. De Loecker acknowledges the fact that if firm-level productivity increases after trade and as a result if firm’s adjust their product mix accordingly, he can not take that into account due to his data limiation. He states that if that happens, due to his data limiations, his work “cannot further sperate the pure productivity effect from product reallocation and selection dimension” (De Loecker 2011, page 1434).

ii. World Trade Organization (WTO) Data Base: Tariff Data

The tariff data is taken from the World Trade Organization (WTO) Tariff Analysis Online. Tariff Analysis Online provides access to two main WTO data bases (i) the Integrated Database (IDB, which contains general information on applied tariffs and imports) and (ii) Consolidated Tariff Schedules (CTS, which includes members’ binding commitments on maximum tariffs).

This data base provides time, country and product wise tariff rates imposed on various products ranging from HS-2 digit till HS-6 digit code. For each product, it reports the tariff line duties, average tariffs, principal suppliers, duty comparison, tariff concessions, tariff quotas etc. In our paper, we specifically narrow down our case to China and Pakistan focusing mainly on the Free Trade Agreement between the two countries.

For the tariffs, we create a composite variable of tariffs at the firm level by aggregating the product level tariffs based on the products produced by firm \(i\) at time \(t\). Where

\[
tariff_{fi} = \sum a_{ijt} \cdot tariff_{fjt} \quad (27)
\]

Where the tariff faced by firm \(i\) at time \(t\) \((tariff_{fi})\) is a summation of the tariff rates imposed on product \(j\) at time \(t\) \((\tau_{jt})\). The tariff rates are added up by weighing the product-level tariff rates according to the share of product \(j\) in the production mix of the firm \(i\) at time \(t\) \((a_{ijt})\). In equation (22) we directly use the product-level tariffs \((tariff_{fjt})\) to instrument for the product level prices \(p_{jit}\) for product \(j\) by firm \(i\) in time \(t\).

Observing the product mix of firms for each time period gives us an added advantage over here as well. Since we observe the product mix change over time, we have more variation in tariff rates faced by firms and we can adjust their exposure to tariff by changing the weights \(a_{ijt}\) as we observe the product share for each year. De Loecker, however, due to his data limitation holds these weights as constant, which again is a

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19 Retrieved from the link: http://tariffanalysis.wto.org

20 Since the tariffs are made available using the HS codes to identify the products, it was important for us to convert our product codes from PSIC into comparable HS codes used at the international level.

21 The maximum we can go in our case is till HS-5 digit code based on our identification of products.
debateable assumption given our discussion of the evolution of textile firms in the product choice under the discussion of the CMI data.

Figure 2 above shows the tariff rates over time for the 5 segments within the textile sector. Overall, we see a decline in the tariff rates imposed by China in all of the segments particularly in the period of 2005-2006, when Pakistan and China entered into the Free Trade Agreement (FTA).

It's worth noting, that although we present the aggregate tariff rate trends in the figure above, we actually use the more disaggregated product wise tariff rates. It is this variation in the product wise tariff rates which then provides variation at the firm level for tariffs in our data set. For example, the tariffs imposed on cotton bed linen went from 21% in the year 2000 to 14% in year 2010 while the tariff rates imposed on babies’ cotton garments and clothing accessories increased from 0% in the year 2000 to 14% in the year 2010.

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We use the actual tariff rates at the product level and hence sum them up at the firm level using weights as described above. We also differ in this case with respect to De Loecker in two ways (i) he mainly looks at the quota restrictions while we look at tariff rates (ii) in aggregating at the firm level, he simply takes the quota restriction to be 1 if the product faces quota restriction and 0 otherwise rather than taking the amount of quota restriction. Hence, the value is 0 if not a single product faces quota restriction and is 1 if all the products face quota restriction. We instead of taking a dummy for tariffs imposed on a product use the actual tariff rates to have more variation in our data. We believe this is important to do so since there is a huge variation in the changes in the tariffs amongst products themselves, even within the same year.
iii. UN Comtrade Data Base

We use the UN Comtrade Data to construct the total segment specific output. The UN Comtrade data by the United Nations is an International Trade Statistic Database. Containing over more than 3 billion data records, it covers over more than 170 countries since 1962. It contains detailed trade statistics based by product categories and trading partners. The product-level trade values (both import and export values) are converted into US $, where the exchange rate is provided by the reporter countries or monthly market rates. Quantities of the products traded are also available in metric units. The products in the UN Comtrade Database are available using the HS coding and which goes up to HS-6 Digit codes. The dataset is publicly available online.

Based on De Loecker’s classification of the textile sector into five different segments, we look at the total demand for these segments in the Chinese market. Based on De Loecker’s specification, we include imports as well. Since China is the relevant market, we consider the total demand in the Chinese market by considering both the total domestic production in China and total imports i.e.

\[ Q_t = Q_t^{china} + Q_t^{imports} \]

\( Q_t^{imports} \) is directly available from the UN Comtrade Database. The main issue was with estimating the output produced by China \( Q_t^{china} \) since we do not have access to Chinese manufacturing data. For this we rely on China’s world export and its export to GDP ratio i.e.

\[ Q_t^{Export} = \omega_t Q_t^{china} \]

Where \( Q_t^{Export} \) is the amount China exports to the world which is a fraction of the amount it produces itself \( Q_t^{china} \). We take this fraction \( \omega_t \) to be the export to GDP ratio of China at time \( t \).

According to this, the amount China produces can be calculated as

\[ Q_t^{china} = \omega_t^{-1} Q_t^{Export} \]

\[ \text{As in the case of the tariff data made available by the WTO, the data made available by the UN Comtrade Database also identifies the products using the HS codes, hence it was essential for us to convert our products into comparable HS codes.} \]

\[ \text{Since the trade values available are in dollars, we convert them into Pakistani Rupees, since our measurement of inputs are in rupees.} \]
We can also get the data on $Q_t^{Export}$ from the UN Comtrade Database\textsuperscript{25}. This gives us our total textile and segment-wise outputs\textsuperscript{26}.

iv. All Pakistan Textile Mills Association (APTMA)

We use the price data available from the All Pakistan Textile Mills Association (APTMA) to construct the sectoral deflator. We need this data to deflate the revenues and hence get the deflated output needed to be used in De Loecker’s method to study the extent of the omitted price bias. APTMA is largest Pakistani national trade association of textile representing around 396 textile mills in the country. APTMA compiles statistics and economic data on textile firms which is then published in the Chairman’s Annual Review to give the updates on the textile sector, its production levels, marketing trends, etc. Much of their data is publicly available on their website. APTMA has detailed section on the textile products being traded. They also report the unit value of various products including cotton yarn, cotton cloth, tents and canvas, bags, towels, bed wear, garments, hosiery etc. The prices are available from the year 1995-2017. We calculate the Producer Price Index using this data with the with the product weights based on the year 2010.\textsuperscript{27}

![Table 4: Producer Price Index (PPI)](image)

<table>
<thead>
<tr>
<th>Year</th>
<th>Price Index</th>
</tr>
</thead>
<tbody>
<tr>
<td>1996</td>
<td>100.00</td>
</tr>
<tr>
<td>1997</td>
<td>95.19</td>
</tr>
<tr>
<td>1998</td>
<td>83.79</td>
</tr>
<tr>
<td>1999</td>
<td>76.82</td>
</tr>
<tr>
<td>2000</td>
<td>71.28</td>
</tr>
<tr>
<td>2001</td>
<td>67.95</td>
</tr>
<tr>
<td>2002</td>
<td>71.62</td>
</tr>
<tr>
<td>2003</td>
<td>79.35</td>
</tr>
<tr>
<td>2004</td>
<td>80.50</td>
</tr>
<tr>
<td>2005</td>
<td>79.22</td>
</tr>
<tr>
<td>2006</td>
<td>83.86</td>
</tr>
<tr>
<td>2007</td>
<td>89.43</td>
</tr>
<tr>
<td>2008</td>
<td>84.96</td>
</tr>
<tr>
<td>2009</td>
<td>86.83</td>
</tr>
<tr>
<td>2010</td>
<td>116.22</td>
</tr>
<tr>
<td>2011</td>
<td>111.47</td>
</tr>
</tbody>
</table>

\textsuperscript{25} Data on the export to GDP ratio is retrieved from : https://www.theglobaleconomy.com/China/Exports/

\textsuperscript{26} It’s worth noting that our estimate of $Q_t^{China}$ is slightly different than that of De Loecker. Since he considers EU as a relevant market for Belgian products he can take use to the firm-level Belgian data to construct the total output produced in EU i.e. $Q_t^{EU}$ in his case, based on the fact that Belgium produces a proportion of the total EU output.

\textsuperscript{27} Although we do see APTMA reporting prices but they are not available based on the HS code. They are also not disaggregated at a narrower product level. For example, it reports the average unit value of garments from 1995-2017 on a yearly basis as an aggregate rather than dividing into products which fall within the garment category.
Analyzing the PPI for the textile sector in Table 4 we see that the PPI falls from 1996-2001 and fluctuates between other years, rising after 2010. It is interesting to note that the PPI for the textile sector shows a different and divergent trend as compared to the PPI of the manufacturing sector as a whole. In relative terms, the aggregate PPI for all manufacturing sector as a whole went up, while our calculations specifically for the textile sector show that remained depressed until 2009, as compared to the base year. This suggests a potential relationship between producer prices and tariff rate changes. This signifies the need to observe prices at the product level for a correct analysis as compared to relying on deflated output as a proxy for actual output since deflators only control for aggregate price shocks. As the changes in tariffs vary according to the products, using deflators does not take this individual variation into account as prices are not available at the product level.

**VI. Results and Discussion**

In this section, we discuss the direction of the bias due to the omitted price bias and simultaneity bias by comparing the coefficients of the production function. We demonstrate the changes in segment elasticities once we control for the demand shocks. We also test De Loecker’s method of controlling for demand shocks and prices by relying on deflated output by comparing the estimates with those based on actual physical output and actual demand shocks. Finally we look at the impact of tariffs on firm-level productivity both at the aggregate level and at the segment level.

**i. Production function estimates and biases**

In this sub-section, we look at the direction of the bias as a result of relying on deflated output. We see what happens when we control for simultaneity bias and omitted price bias individually, and finally when we control for them together.

In column (1) of table 5, we present the OLS results where we use deflated output to estimate the production function. In column (2) instead of using deflated output, we take advantage of the disaggregated price and output data and use the actual output as our dependent variable instead. In column (3) we use the deflated output but we control for the simultaneity bias by using the LP method. Finally in column (4) try to control for both omitted price bias and simultaneity bias. We control for the simultaneity bias by using LP method while we control for the price by adding in one demand parameter i.e. the aggregated demand faced in the textile sector.
Going from specification (1) to (2) corrects for the downward bias in the input coefficients. Our coefficients in specification (2) go up for all of the inputs as compared to specification (1). Our results are in line with the literature in this context. According to Klette & Griliches (1996), using deflated output as a proxy for real output, cetris paribus, leads to a downward bias in the production function coefficients. Firms with high costs, will charge higher prices and hence lose out on market share. These idiosyncratic changes in factor inputs suggest a negative relation between firms price and changes in input levels, suggesting a downward bias. Moreover, if firms experience productivity growth, they will charge a lower price and obtain a large market share. More output may not mean more input for productive firms, but when the demand in elastic, the increase in output tends to exceed the gain in productivity, implying the usage of more inputs, again suggesting a negative relationship between inputs and prices, leading to a downward bias in the estimates.

Comparing specification (1) with (3), we control for the simultaneity bias. The omitted price bias isn’t addressed in this specification. The labor coefficient is somewhat lower than in specification (1) while the coefficient of capital goes up slightly. According to Olley & Pakes (1996) firms with larger capital stock can expect larger returns in future at
any given level of current productivity and hence may continue to operate at lower levels of productivity. Hence by this self-selection, the expectation of productivity will be decreasing, the higher the capital is, leading to a negative bias in the capital coefficient.

We address both the biases in specification (4). We use the LP method to correct for the simultaneity bias and control for aggregate demand of the textile industry (including imports) to control for demand and prices, while still relying on deflated revenue. We can see that since the direction of the omitted price bias and simultaneity bias works in the opposite direction. Our results for specification (4) are somewhat in between our coefficients for specification (2) and (3), which corrects for them individually. Since we control for the demand parameter, we obtain α’s as discussed under section III.

ii. Price and Demand effects: Measuring Segment Elasticity and testing De Loecker’s Approach

In this subsection we run the complete model and specifically focus on the elasticities of different segments within the textile sector. We start by presenting the results under De Loecker’s model both with and without controlling for demand shocks, while still relying on deflated output as our dependent variable. We then compare the results with the estimates we get using actual output data. Finally, we compare the results under both specifications with the results we get using our data in the most disaggregated way i.e. using actual output and actual demand shocks as described under section IV.

Results are presented in table 6. Column (1) –(4) use De Loecker’s method. De Loecker relies on product and product-group effects, including firm specific protection measure (in our case tariffs) to control for the unobserved demand shocks. It is interesting to note that the segments which are the most elastic in our case i.e. interior and clothing are also the most protected segments (refer back to figure 2). This indicates a positive correlation between segment demand variables ($q_{st}$) and the error term, which contains the variation in the tariff rates.

Our estimates support De Loecker’s argument regarding the importance of controlling for demand shocks in the analysis. Moving from column (1) to (3) we can see that once we control for demand parameters, the coefficients fall and as a result, the estimates of elasticities go up. It is worth noting the importance of controlling for the unobserved demand shocks over time by including product and product-group controls, which are in fact a reflection of consumer tastes. The industry’s overall elasticity increases from -1.92 to -3.33 when we take the complete model into account. Controlling for the demand shocks makes all the textile segments more elastic, with the biggest impact being on the relatively more elastic segments. For example, the elasticity of the clothing segment goes from -1.88 to -2.17.

In column (5) to (8), we use the actual output as the dependent variable while still relying on De Loecker’s method of controlling for unobserved demand shocks by using product
and product-group controls, along with tariffs as an exogenous trade protection measure. It is interesting to note that even if we do not control for demand shocks, but if we just use the actual output rather than deflated output, we get higher elasticities (column (2) in comparison with column (6)). This clearly indicates the presence of the uncorrected “omitted price bias” introduced by relying on the sectoral deflator.

Using the actual output data, when we incorporate the demand controls and hence the entire nested demand model, estimates of $\beta$’s go down and segment elasticities become more elastic. This is an essential finding in the sense that even if we have the actual output data, if we still do not control for the demand shocks, we will still get estimates that are a mix of demand shocks and productivity shocks. In order to measure the “actual productivity” it is essential for us to control for the demand shocks, even when actual disaggregated price-output data is available. This is mainly because prices, even if observed separately, may contain both demand and supply variations. In order to estimate the actual productivity measure and the true coefficients we need to control for the unobserved demand shocks. This result supports the work done Pozzi & Schivardi (2016) where they argue that studies focusing narrowly on productivity might not measure the actual productivity since the estimates derived might turn out to be a mix of productivity and demand shocks. If prices reflect market demand, than the common connection of productivity and firm growth might be overestimated and the impact of demand side factors that matter for growth might be understated. Hence, disentangling both the productivity and demand shocks is important.

Finally in the last two columns we present the results of measuring the actual demand shocks of firms at the product level by taking the full advantage of our disaggregated price and output data. Hence, instead of relying on the product and product group dummies we compute the actual demand shocks as mentioned in section IV. We believe these are the most accurate results since we use the data in the most disaggregated form. We use tariff rate at the product level to instrument for prices. Appendix B represents the results obtained by equation (22) and (23). Our results from table 6 for this specification are the most elastic as can be seen by column (9) and (10).

It’s important to note that if we compare the estimate of elasticities under column (2) with those under (10), we see huge changes in elasticities. The industry’s elasticity goes from -1.92 to -5.55. For the interior segment the elasticity jumps from -2.32 to -7.14 while for the clothing segment it goes from -1.88 to -4.0.

Much of the literature that is present in the area of productivity, evaluating the impact of trade or any other policy change on firm level productivity mainly relies on deflated output and does not control for demand shocks, which is what is done under column (1) and (2). Comparing the elasticities under column (2) with those under (10), we can see the importance of both correcting for the omitted price bias by using actual output and controlling for actual demand shocks in our estimates. This confirms both Klette &
Griliches (1996) concern regarding the omitted price bias and De Loecker’s (2011) concern regarding the importance of incorporating demand shocks in the literature of productivity.

Next comparing De Loecker’s method of controlling for demand shocks under column (3) and (4), we can see that they do improve the results as compared to column (1) and (2) since they are much closer to the actual coefficients presented under column (9) and (10). Hence our findings go in support of De Loecker’s methodology. In the absence of disaggregated price-output data, it is essential to control for demand shocks, and the methodology developed by De Loecker does contribute towards improving the estimates as compared to column (1) and (2).

Comparing our estimates of using actual output as shown under column (5) to (8) with that under column (9) and (10) has two main implications. First using actual output rather than deflated output (as compared to column (1) and (2)) and hence correcting for the omitted price bias does improve our estimates. But as pointed out by Foster, et al., (2008) even if we observe prices, they might not just reflect productivity changes but rather demand changes and hence we need to take them into account. Once we do that and move on the column (7) and (8), where we correct for both the omitted price bias and unobserved demand shocks we get estimates which are in fact very close to the estimate obtained under column (9) and (10). This means that De Loecker’s method of controlling for demand shocks by using product and product-group dummies works really well, only if we have actual output rather than deflated output. Or put another way, if we are able to measure the deflated output as accurately as possible, the closer we move from column (3) and (4) to column (7) and (8), we can improve our estimates. The only difference between these columns is the dependence on deflated output and actual output, while both rely on De Loecker’s method of controlling for demand shocks. Hence, if we can somehow correct for the “omitted price bias” introduced by using a sectoral deflator, we get estimates which are very close to the actual ones. Correcting for the price bias together with relying on De Loecker’s method of demand shocks works very well.

So, if we control for demand shocks relying on De Loecker’s method, the main problem is then how accurately we estimate the output and ultimately how accurate is the sectoral deflator. In other words, how can we move from column (3) and (4) towards (7) and (8) with the only difference being the use of actual output. Hence, if a good deflator can be found to address this, one may not even need to estimate the actual productivity shocks as done under specification (9) and (10). In other words, the accuracy of De Loecker’s method is sensitive to the deflator used.

Using a sectoral deflator is problematic. Neither does it consider the price variation across different firms, nor does it account for the price variation within a firm producing heterogeneous products. Figure 3a-3d demonstrates the wide variation in product prices for the year 2005.
Figure 3a shows the price variation for women’s shirts and blouses. Even within the same year, i.e. 2005, we see a lot of dispersion amongst the prices for the same product. Prices for women’s shirts and blouses are clearly not normally distributed, being as low as less as PKR 1000 to as high as above PKR 5000. We can see wide variation in the prices for other products as well including curtains and drapes, fabrics of nylon and carpets and other textile coverings.

Not only do we see significant dispersion in the prices for the same product for a given year, we also see significant dispersion in prices across products and hence segments, even within the same year. Women’s shirts and blouses and curtains (including drapes), for example, are in 1000’s of PKR, while tyre cord fabrics and carpets measured in meters are in 100’s of PKR. Having the same deflator for both the product will then clearly lead to biased results.

28 1 US $ equals to around 150 Pakistani Rupee (PKR).
29 We randomly pick products for 2005 in this case. We see a similar dispersion in prices even if we choose different products or different years.
Table 6: Segment Specific Demand Elasticities and Returns to Scale under different specifications

<table>
<thead>
<tr>
<th></th>
<th>Deflated Output</th>
<th>Actual Output</th>
<th>Actual Output and Actual Demand Shocks</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Without Demand Dummies</td>
<td>With Demand Dummies</td>
<td>Without Demand Dummies</td>
</tr>
<tr>
<td>β Elasticity</td>
<td>β Elasticity</td>
<td>β Elasticity</td>
<td>β Elasticity</td>
</tr>
<tr>
<td>Industry</td>
<td>0.52**</td>
<td>-1.92</td>
<td>0.30**</td>
</tr>
<tr>
<td>Technical</td>
<td>0.74***</td>
<td>-1.35</td>
<td>0.64***</td>
</tr>
<tr>
<td>Spinning</td>
<td>0.54**</td>
<td>-1.85</td>
<td>0.51**</td>
</tr>
<tr>
<td>Clothing</td>
<td>0.53***</td>
<td>-1.88</td>
<td>0.46***</td>
</tr>
<tr>
<td>Finishing</td>
<td>0.90***</td>
<td>-1.11</td>
<td>0.81***</td>
</tr>
<tr>
<td>Interior</td>
<td>0.43**</td>
<td>-2.32</td>
<td>0.38**</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Inputs</th>
<th>β</th>
<th>α</th>
<th>β</th>
<th>α</th>
<th>B</th>
<th>α</th>
<th>β</th>
<th>α</th>
<th>β</th>
<th>α</th>
</tr>
</thead>
<tbody>
<tr>
<td>Capital</td>
<td>0.09**</td>
<td>0.19</td>
<td>0.09***</td>
<td>0.13</td>
<td>0.10**</td>
<td>0.20</td>
<td>0.07**</td>
<td>0.10</td>
<td>0.09***</td>
<td>0.11</td>
</tr>
<tr>
<td>Labor</td>
<td>0.13**</td>
<td>0.27</td>
<td>0.20**</td>
<td>0.29</td>
<td>0.15**</td>
<td>0.29</td>
<td>0.17**</td>
<td>0.22</td>
<td>0.19**</td>
<td>0.23</td>
</tr>
<tr>
<td>Materials</td>
<td>0.58***</td>
<td>1.21</td>
<td>0.56***</td>
<td>0.80</td>
<td>0.46***</td>
<td>0.91</td>
<td>0.60***</td>
<td>0.77</td>
<td>0.59***</td>
<td>0.72</td>
</tr>
</tbody>
</table>

| RTS              | 1.7  | 1.2  | 1.4  | 1.1  | 1.1  | 1.1  | 1.1  | 1.1  | 1.1  | 1.1  |
Figure 3a-3d: Product wise prices for the year 2005

Figure 3a

Figure 3b

Women's or girls' blouses, shirts and shirt-blouses, knitted or crocheted other than cotton or man-made fibre

Curtains (including drapes) and interior blinds; curtains or bed valances; of cotton
Figure 3c

Tyre cord fabrics of high tenacity yarn of nylon or other polyamides, polyester or viscose rayon: other

Figure 3d

Carpets and other textile floor coverings: including "Kelem", "Schumacks", "Karamanie" and similar hand woven rugs
iii. **Impact of Tariff on Aggregate Firm Productivity**

This section shows the results from specification (20) under which we look at the impact of tariffs on firm level productivity. Once we have all the model parameters under different specifications as described previously, we can estimate productivity as under equation (19).

Table 7 presents the results below. As expected, we get negative sign in all the specifications, since high tariffs reduce firm level productivity. We start with estimating productivity by taking equation (1) to the data, computing the residuals as the productivity, using OLS. This does not control for any of the two biases (simultaneity bias and omitted price bias) nor for the demand shock. Results show that a 10% reduction in tariffs increases firm’s productivity by 3.35%.

Contrast to this, all other specifications below control for simultaneity bias where we apply a two-step GMM approach using materials as a proxy for productivity. The only difference amongst the remaining specifications is the extent to which we control for the biases by using deflated output versus actual output and if we control for demand shocks or not.

<table>
<thead>
<tr>
<th>Specification</th>
<th>$\beta$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Deflated Output with OLS</td>
<td>$-0.335^{***}$ $(0.4383)$</td>
</tr>
<tr>
<td>Deflated Output</td>
<td></td>
</tr>
<tr>
<td>• Without Demand Dummies</td>
<td>$-0.081^{***}$ $(0.0099)$</td>
</tr>
<tr>
<td>• With Demand Dummies</td>
<td>$-0.049^{***}$ $(0.0059)$</td>
</tr>
<tr>
<td>Actual Output</td>
<td></td>
</tr>
<tr>
<td>• Without Demand Dummies</td>
<td>$-0.054^{***}$ $(0.0043)$</td>
</tr>
<tr>
<td>• With Demand Dummies</td>
<td>$-0.033^{***}$ $(0.0029)$</td>
</tr>
<tr>
<td>Actual Demand Shocks</td>
<td>$-0.023^{***}$ $(0.0068)$</td>
</tr>
</tbody>
</table>

Robust Standard Error in Parenthesis.
*** Significant at 1%.

In the specifications using deflated output, we test for De Loecker’s approach. Clearly we can see that controlling for demand shocks reduces the impact of tariff, where the impact of a 10% reduction in tariffs goes from 0.8% to 0.5% on firm level productivity, once the
demand shocks are controlled. This specifies the need to incorporate the demand shocks as the impact nearly halves.

Moving on to our estimates which use the actual output instead of deflated output, we again see that incorporating demand shocks reduces the magnitude of the impact of tariffs on firms productivity, where a 10% reduction in tariff improves productivity by 0.3% as opposed to 0.5% when demand shocks are incorporated.

The last row shows the impact of tariffs on productivity using actual demand shocks, computed by taking the full advantage of the disaggregated price-output data. Exogenous tariff rates were used to instrument for prices, where the demand shocks are calculated at the product level and aggregated at the firm level as under section IV. We believe this to be the most accurate measure since it incorporates data in the most disaggregated form.

Comparing our results, the first thing we conclude is a large bias in the estimation of productivity when we compare our results from OLS to the actual demand shocks. If we fully control for the simultaneity bias, omitted price bias and demand shocks, a 10% reduction in tariffs only boosted firm level productivity up by 0.2% as opposed to 3.35% as suggested by the OLS results.

Next we can see that controlling for demand shocks is important. Under De Loecker’s method if we control for demand shocks, the magnitude falls to nearly half from -0.08 to -0.049, suggesting that controlling for simultaneity bias isn’t enough, we need to take the demand shocks into account. We see similar results when we compare the estimates obtained using actual output. If we just correct for the omitted price bias along with the simultaneity bias, a 10% reduction in tariffs improves productivity by 0.5% but when we take into account the demand shocks the magnitude falls to 0.33%. Hence, our results support the literature available on demand and stress on the importance of controlling for demand shocks along with simultaneity bias and omitted price bias.

Our results show that if we have actual output and we use De Leocker’s method to control for demand shocks, we get a coefficient of -0.033 which is the closest to the actual impact of -0.023. Hence if we can improve on the sectoral deflator and get the deflated output to be as close as possible to the actual output, we can apply De Loecker’s method and get estimates which are very close to the actual ones.

**iv. Impact of tariffs on Segment-Wise Firm Level Productivity**

In this sub-section, we look at the impact of tariffs on firm level productivity based on a segment analysis. Figure 3 shows that in terms of the exports to China, spinning remains the most important segment followed by finishing. This is no surprise given the tariff rates imposed by China as shown under figure 2.
Table 8 below shows the results of the impact of tariffs on firm level productivity in a segment wise analysis. We see a similar trend for all the segments under various specifications.

![Figure 3: Pakistan's Segment Wise Exports to China (US $)](image)

<table>
<thead>
<tr>
<th>Specification</th>
<th>Segment</th>
<th>Spinning</th>
<th>Finishing</th>
<th>Interior</th>
<th>Clothing</th>
<th>Technical</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>4</td>
<td>5</td>
</tr>
<tr>
<td><strong>Deflated Output</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Without Demand Dummies</td>
<td></td>
<td>-0.275***</td>
<td>-0.217***</td>
<td>-0.116***</td>
<td>-0.197****</td>
<td>0.078</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.0092)</td>
<td>(0.0402)</td>
<td>(0.0148)</td>
<td>(0.0563)</td>
<td>(0.0534)</td>
</tr>
<tr>
<td>With Demand Dummies</td>
<td></td>
<td>-0.220***</td>
<td>-0.166***</td>
<td>-0.071***</td>
<td>-0.041***</td>
<td>0.021</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.0042)</td>
<td>(0.0160)</td>
<td>(0.0054)</td>
<td>(0.0062)</td>
<td>(0.0239)</td>
</tr>
<tr>
<td><strong>Actual Output</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Without Demand Dummies</td>
<td></td>
<td>-0.187***</td>
<td>-0.152***</td>
<td>-0.109***</td>
<td>-0.145***</td>
<td>0.063</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.0063)</td>
<td>(0.0265)</td>
<td>(0.0300)</td>
<td>(0.0099)</td>
<td>(0.0575)</td>
</tr>
<tr>
<td>With Demand Dummies</td>
<td></td>
<td>-0.183**</td>
<td>-0.141***</td>
<td>-0.061***</td>
<td>-0.036***</td>
<td>0.017</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.0848)</td>
<td>(0.0103)</td>
<td>(0.0219)</td>
<td>(0.0122)</td>
<td>(0.1124)</td>
</tr>
<tr>
<td><strong>Actual Demand Shocks</strong></td>
<td></td>
<td>-0.181***</td>
<td>-0.113***</td>
<td>-0.050***</td>
<td>-0.037***</td>
<td>0.0046</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.0052)</td>
<td>(0.0161)</td>
<td>(0.0047)</td>
<td>(0.0035)</td>
<td>(0.0211)</td>
</tr>
<tr>
<td><strong>N</strong></td>
<td></td>
<td>784</td>
<td>220</td>
<td>157</td>
<td>446</td>
<td>94</td>
</tr>
</tbody>
</table>

Robust Standard Error in Parenthesis.
*** Significant at 1%.
The impact of tariffs on the technical segments remains insignificant for all the specifications. The highest impact of a 10% tariff reduction is on spinning segment followed by the finishing. A 10% tariff reduction leads to an 18% increase in productivity for firms active in the spinning segment while it leads to an 11% increase in productivity for firms operating in the finishing segment. As can be seen by figure 3, our results confirm that the impact of tariff reductions on firm’s productivity has been the most for the top two exporting segments to China, for which the tariffs are the lowest (refer to figure 2).

v. The net impact of FTA on firm level productivity

In this section we look at the net impact of the FTA on firm level productivity by taking the changes in tariff rates into account from 2000 till 2010 as shown under figure 2.

Table 9 presents the results. We get very similar results to De Loecker’s (2011) study in this context. According to the OLS results complete tariff elimination leads to a 32% improvement in firm level productivity. However, when we control for simultaneity bias and use De Loecker’s method the impact falls to around 8%. When we control for the demand shocks the impact of tariffs falls to merely 5%. The impact of the FTA using De Loecker’s method reduces the impact of tariff elimination by 7 fold (32% to 4.7%). Within De Loecker’s method, just controlling for the demand shocks reduces the aggregate impact of the FTA from 7.8% to 4.7%, nearly halving the impact. Hence again, the results point out on the importance of controlling for both the simultaneity bias and price bias, along with incorporating the demand shocks.

<table>
<thead>
<tr>
<th>Specification</th>
<th>Impact</th>
</tr>
</thead>
<tbody>
<tr>
<td>OLS</td>
<td>0.322</td>
</tr>
<tr>
<td>Deflated Output</td>
<td></td>
</tr>
<tr>
<td>• Without Demand Dummies</td>
<td>0.078</td>
</tr>
<tr>
<td>• With Demand Dummies</td>
<td>0.047</td>
</tr>
<tr>
<td>Actual Output</td>
<td></td>
</tr>
<tr>
<td>• Without Demand Dummies</td>
<td>0.052</td>
</tr>
<tr>
<td>• With Demand Dummies</td>
<td>0.032</td>
</tr>
<tr>
<td>Actual Demand Shocks</td>
<td>0.022</td>
</tr>
</tbody>
</table>

Comparing our estimates using De Loecker’s approach while relying on deflated output versus the actual output, we can see that the impact falls when we use the actual output. However, even when using the actual output, we still need to incorporate the demand shocks into account. Incorporating the demand shocks using De Leocker’s method using actual output shows the net impact of the FTA has been 3%, which is very close to the most reliable result based on using actual demand shocks of 2%.
Since most of the literature relies on aggregated revenue data, De Loecker’s method works well provided we have a reliable deflator which moves our dependent variable to be as close as the actual output.

In table 10 below, we present the results of the total impact of the FTA on the segment wise firm productivity. We only show the impact of using actual demand shock specification in this case. Our results are in line with those under table 8, where the biggest impact has been for the spinning segment.

<table>
<thead>
<tr>
<th>Segment</th>
<th>Impact</th>
</tr>
</thead>
<tbody>
<tr>
<td>Spinning</td>
<td>0.167</td>
</tr>
<tr>
<td>Finishing</td>
<td>0.065</td>
</tr>
<tr>
<td>Clothing</td>
<td>0.017</td>
</tr>
<tr>
<td>Technical</td>
<td>-0.004</td>
</tr>
<tr>
<td>Interior</td>
<td>0.024</td>
</tr>
</tbody>
</table>

All coefficients are significant (at 1% LOS) except for the Technical Segment. We only present the results of using actual demand shocks in this table.

Elimination of tariffs under the FTA has improved the productivity under the spinning segment by 16%, while it has improved the productivity of the finishing segment by 6%. The lowest impact is for clothing and interior (1.7% and 2.4% respectively) which are the most elastic and the most protected segments. This confirms the productivity gains for the least protected segment by China.
VII. Conclusion

This study explores the trade-productivity linkage under the Free Trade Agreement between Pakistan and China. We look at the impact of tariff reductions on the productivity of textile firms in Punjab, Pakistan. In doing this, special emphasis has been given to the measurement issues with productivity. We enjoy the benefits of having a unique data set which gives us disaggregated price and output information not only at the firm level but at the product level. This enables us to incorporate both the input simultaneity bias and the omitted price bias in our estimates of productivity. Observing disaggregated data gives us an additional benefit of estimating the demand shocks in a very precise manner, which are then controlled for in our estimate for productivity. This disaggregated data gives us the actual productivity estimates as opposed to measured productivity. The actual productivity is the measured productivity net of price and demand variations.

We then compare our results to those obtained under the methodology developed by Jan De Loecker (2011) who controls for both type of bias while still relying on firm revenue data and sectoral deflators. He does this by introducing demand shifters and relying on exogenous trade policy changes.

Our results indicate that there is a substantial bias if we just rely on OLS estimates of productivity. We get evidence in support of De Loecker’s methodology, in cases where disaggregated data is missing, provided that we have good deflators which gives us deflated output which is close to the actual output. Relying on weak deflators will still give us biased results since it will not completely omit the price bias. Weak deflators will fail to take into account the significant price dispersion both within and across firms. Our results also demonstrate that it is essential to incorporate demand shocks when taking into account the impact of any policy measure on productivity including trade.

Addressing both types of biases and incorporating the demand shocks in the most precise manner makes the textile segments more elastic as compared to the other methodologies. The impact of 10% reduction in tariffs on firm level productivity falls from 3.35% to 0.2% when we use our estimates of actual productivity. The net impact of the FTA on firm level productivity drops from 32% to only 2% when we use our actual productivity measures. Interestingly, the impact of the FTA has been the largest on the spinning segment within the textile sector, which is also the least protected segment.

Overall, our analysis illustrates the sensitivity of firm-level estimates of productivity to the quality of data used as well as the critical role of demand shocks when estimating the impact of policy changes on productivity. Only if these factors are taken into account will policymakers be able to obtain accurate estimates of the impact of past and planned policy changes on productivity.
References


Appendix A: Classification of Segments based on De Loecker’s classification

<table>
<thead>
<tr>
<th>Segment</th>
<th>Classification</th>
</tr>
</thead>
</table>
| Spinning | • Blended polypropylene or chloro fiber yarns  
| | • Filament yarns  
| | • Blended yarns  
| | • Blended polyester yarns  
| | • Blended cotton or linen yarns  
| | • Blended artificial yarns  
| | • Blended aramid, polyamide, or polyacrylic  
| | • Spun yarns (>85% of 1 fiber) |
| Finishing | • Material before Spinning  
| | • Knitted Fabrics  
| | • Carpeting  
| | • Yarn  
| | • Nonwoven  
| | • Specialties |
| Clothing (Fabrics and Knitwear) | • Baby & children’s clothes  
| | • Accessories  
| | • Fabrics for nightwear, outerwear, sportswear  
| | • Children’s wear  
| | • Men’s wear  
| | • Bath  
| | • Babies’ wear  
| | • Women’s wear  
| | • Underwear  
| | • Nightwear & underclothing  
| | • Rainwear, sportswear, & leisure  
| | • Stockings, tights, socks  
| | • Other Fabrics |
| Technical | • Build tech  
| | • Geo tech  
| | • Indu tech  
| | • Med tech  
| | • Mobli tech  
| | • Pack tech  
| | • Pro tech  
| | • Sport tech  
| | • Agro tech |
| Interior | • Carpets  
| | • Kitchen Linen  
| | • Mattress Ticking  
| | • Wall Coverings  
| | • Upholstery and furnishing fabrics’  
| | • Trimmings  
| | • Terry Towel Articles  
| | • Bed Linen |
Appendix B: Results of Equation (22) and (23):

First Stage Result: Instrumenting prices by using actual tariff rates (at the product level)
Dependent variable: Price

<table>
<thead>
<tr>
<th>Tariff</th>
<th>0.468***</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(0.8053)</td>
</tr>
</tbody>
</table>

F. Value of Excluded Instruments: 30.12

Second Stage Result: Instrumenting prices by using actual tariff rates (at the product level)
Dependent variable: Output

<table>
<thead>
<tr>
<th>Prices</th>
<th>-2.015***</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(0.4787)</td>
</tr>
</tbody>
</table>

First Stage results indicate that tariff is a good instrument for prices. A 1% increase in tariffs, increases the price of the output by 0.47%. The F-value of the instrument is also greater than 10, as per the standard rule.

Second stage results indicate the typical law of demand relationship between price and quantity demanded. Using estimated prices from stage 1, we conclude that a 1% increase in the price of a product reduces its demand by 2%. This also indicates the average elasticity of the products within the textile sector.