ESSAY ON FIRMS PRODUCTIVITY IN PAKISTAN

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DOCTOR OF PHILOSOPHY

Nida Jamil
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I certify that I have read this dissertation and that, in my opinion, it is fully adequate in scope and quality to be considered for the degree of Doctor of Philosophy.

Dr. Theresa Chaudhry (Principal Supervisor)

I certify that I have read this dissertation and that, in my opinion, it is fully adequate in scope and quality to be considered for the degree of Doctor of Philosophy.

Dr. Azam Chaudhry (Advisory Committee Member)

I certify that I have read this dissertation and that, in my opinion, it is fully adequate in scope and quality to be considered for the degree of Doctor of Philosophy.

Dr. Naved Hamid (Advisory Committee Member)

ESSAY ON FIRMS PRODUCTIVITY IN PAKISTAN

by

Nida Jamil

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Abstract

This dissertation is a contribution towards the trade-productivity literature. Using the Free Trade Agreement (FTA) between Pakistan and China in 2006 we identify various dimensions of effects on firm-level productivity, focusing specifically on the textile sector in Punjab, Pakistan. We begin by studying the impact of failing to correct for measurement issues when estimating productivity and its implication on measuring the impact of a policy change (access to export markets). We examine the consequences of not observing detailed micro-level data at the product level and relying on sectoral deflators instead. We also examine the importance of demand shocks in the analysis. Next, we investigate the impact of the FTA on the productivity and quality of firms under the FTA, especially those exporting to China. We also examine how firms respond to the FTA by changing their investment, product scope, and by adjusting markups.

Our results indicate the importance of using disaggregated data in the estimation of productivity to infer *actual* productivity as compared to *measured* productivity. De Loecker's (2011) methodology works well in controlling for omitted price bias provided we have a good sectoral deflator. Moreover, it is essential to control for the demand shocks when studying productivity. The impact of the FTA falls by half when we take demand shocks into consideration. Furthermore, relying on the De Loecker, Goldberg, Khandelwal, and Pavcnik (2016) methodology along with System GMM and Gandhi Navarro and Rivers (2020) approaches, we re-estimate firm productivity using the newest techniques. We also estimate firm product quality based on the approach of Khandelwal (2010). Results show that for the firms exporting to China, the productivity and quality gains have been limited though we do find evidence of geographical spillovers from exporters to non-exporters. Firms as a result of the FTA increase labor and material usage but fail to raise investment. They also reduce their product scope in response to the competition faced in the Chinese market. There were no substantial reductions in firm-level markups or marginal cost. Competition faced by the Pakistani firms from the ASEAN countries who got better access in the Chinese market can be one of the potential reasons for these limited gains.

Thesis supervisor: Dr. Theresa Chaudhry
Supervisor's Title: Professor

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1. Introduction

Pakistan's economy has been struggling in recent years. Inflation is high, energy shortages continue, much of the growth is consumption-led. Importantly for the real economy, Pakistan has missed the current year's industrial targets and the pandemic has shaken the world economy. Yet the current account of the country was in a surplus after 17 years, workers' remittances saw a historically high growth rate of 29% (July-April 2021), and the Pakistan Stock Exchange market earned the title of being the best Asian stock market and the fourth best performing market across the world in 2020 (Pakistan Economic Survey, 2020-21). While Pakistan has missed its growth targets in the past it may now be on the road toward stabilization (Figure 1).

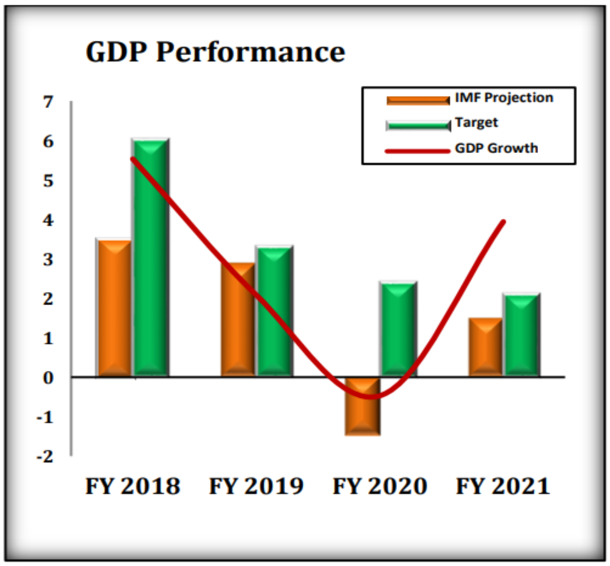

Figure 1
Source: Pakistan Economic Survey 2020-21.

In this still tenuous situation, one needs to carefully analyze what is happening with the various drivers of growth for the economy. One such major driver of growth is productivity. This dissertation uses Pakistani firm-level data to analyze various aspects of firm productivity.

The importance of productivity dates back to when Solow (1957) used US data for 1909-1949 to find that US output per unit of labor had nearly doubled. According to Solow, one-eighth of the total increase was due to increase in capital per worker while the remainder was due to the "Solow residual", also referred to as the total factor productivity (TFP), which indicates that this component, unattributed to any particular measured input, is quite large. Hall and Jones (1999) further provided evidence of this relationship, between productivity and growth, by comparing the output per worker differences between the US and Niger. According to them,

> …consider the 35-fold difference in output per worker between the United States and Niger. Different capital intensities in the two

> countries contributed a factor of 1.5 to the income differences, while different levels of educational attainment contributed a factor of 3.1. The remaining difference- a factor of 7.7 -remains as the productivity residual.
>
> Hall and Jones (1999)

A vast literature focuses on economic policies and their impact on firm productivity. One important relationship often studied is the one between trade and productivity. This dissertation contributes to the literature that looks at the relationship between trade and productivity. We specifically focus on the Free Trade Agreement between Pakistan and China and its impact on textile manufacturers in Punjab, Pakistan. Table 1a-1b below show that while Pakistan exports 9.7% of its total exports to China, it receives 27.1% of its total imports from China, with China being the top importing country for Pakistan (as of 2020-21). Given the large volumes of trade, the Pakistan China Free Trade Agreement is of great importance for the future of the Pakistani economy. In the wake of this FTA, we study various aspects of productivity growth.

Table 1a: Major Export Markets of Pakistan (Rs Billion & Percentage Share)

Country	2017-18		2018-19		2019-20		July-March			
							2019-20		2020-201P	
	Rs	% Share	Rs	% Share	Rs	% Share	Rs	% Share	Rs	% Share
USA	400.4	15.7	532.8	17.0	585.4	17.4	471	17.3	593.6	19.7
CHINA	185.7	7.3	259.6	8.3	349.7	10.4	219	8.0	292.9	9.7
AFGHANISTAN	165.2	6.5	176.4	5.6	134.3	4.0	115.6	4.2	126.9	4.2
UNITED KINGDOM	186.7	7.3	226.8	7.3	239.6	7.1	194.7	7.1	245.3	8.1
GERMANY	146.7	5.7	173.4	5.5	199.0	5.9	162.1	5.9	187.7	6.2
U.A.E	104	4.1	125.8	4.0	178.9	5.3	141.6	5.2	118.8	3.9
BANGLADESH	81	3.2	101.8	3.3	102.6	3.0	91.8	3.4	126.9	4.2
ITALY	84.5	3.3	107.4	3.4	115.0	3.4	92.4	3.4	92.6	3.1
SPAIN	104.5	4.1	126.5	4.0	130.3	3.9	109.2	4.0	108.1	3.6
FRANCE	45.5	1.8	53.9	1.7	57.7	1.7	44.8	1.6	49.8	1.6
All Other	1,050.8	41.1	1,243.8	39.8	1,277.3	37.9	1,083.0	39.7	1,077.7	35.7
Total	2,555.0	100.0	3,128.2	100.0	3,369.8	100.0	2,725.2	100.0	3,020.3	100.0

Table 1b: Major Import Markets of Pakistan (Rs Billion & Percentage Share)

Country	2017-18		2018-19		2019-20		July-March			
							2019-20		2020-21 P	
	Rs	% Share	Rs	% Share	Rs	% Share	Rs	% Share	Rs	% Share
CHINA	1,731.8	25.9	1,734.3	23.3	2328	33.1	1,267.2	23.6	1,725.8	27.1
UAE	893.3	13.3	1020.1	13.7	812.7	11.6	759.7	14.1	602.2	9.4
SAUDI ARABIA	356.4	5.3	401.3	5.4	273.6	3.9	286.2	5.3	301.9	4.7
KUWAIT	159.7	2.4	185.8	2.5	178.7	2.5	133.8	2.5	167	2.6
INDONESIA	278.5	4.2	327.3	4.4	339.6	4.8	245.5	4.6	360.6	5.7
INDIA	207.5	3.1	204.8	2.8	59.9	0.9	154.8	2.9	38.3	0.6
U.S. A	316.4	4.7	368.9	5.0	396.7	5.6	259.5	4.8	351.1	5.5
JAPAN	266.5	4.0	246.1	3.3	174.7	2.5	188.0	3.5	173.8	2.7
GERMANY	146.4	2.2	142.6	1.9	124.2	1.8	105.4	2.0	122.2	1.9
MALAYSIA	132	2.0	145.5	2.0	148.3	2.1	103.0	1.9	134.3	2.1
All Other	**2,206.5**	33.0	**2,666.5**	35.8	**2,193.4**	31.2	**1,867.9**	34.8	**2,400**	37.6
Total	**6,695**	100.0	**7443.3**	100.0	**7,029.8**	100.0	**5,371.1**	100.0	**6,377.2**	100.0

Source: Pakistan Economic Survey 2020-21

Literature Review

In this section we review the literature on productivity focusing on its connection with economic growth. We also discuss sources of productivity growth and its linkage with trade.

Productivity and Economic Growth

The macroeconomic literature affirms that, in addition to the known factor inputs, including labor, capital, and materials, the residuals of a growth accounting exercise, typically referred to as the total factor productivity (TFP), are important for long term economic growth. Ismihan & Metin-Ozcan (2009) in their study on Turkey examine the impact of various policies on the TFP growth between 1940-2004. They conclude that stable macro-economic conditions along with investment in infrastructure is crucial for TFP growth. In addition to this, advancements in foreign trade also helps in promoting TFP growth which eventually leads to economic growth.

China's emergence and growth in the world has been very impressive. Wang & Yao (2003) in their study on China examine various sources to explain this growth. They conclude that while factor accumulation, in particular the human capital accumulation has been quite rapid in China and explains an enormous part of its economic growth, the growth in TFP is still an important source. Moreover, in the long run, the potential to enhance the inputs might be limited due to input constraints and population ageing, then, in this case only the TFP growth will be the driving force behind China's future economic growth. Wang et al. (2013) using provincial data of China from 1985-2007 study the growth in the agricultural sector. Their results show that more than 50 percent of China's agricultural growth was due to TFP growth with coastal regions enjoying a faster productivity growth than non-coastal areas. Voskoboynikov (2017) examines the global financial crisis of 2008 in context to the Russian economy. The study concludes that much of the stagnation during

2008-2014 was due to a decline in TFP and poor allocation of labor rather than the lack of capital input. Aghion, Comin, & Howitt (2016) find that lagged savings are significantly related with productivity growth for poor countries and that the effect operates entirely through TFP rather than capital accumulation. Singh (2017) in his study on India finds that the states which recorded positive TFP growth were the ones which ultimately had massive infrastructure improvements. Neira (2019) examines a sample of the OECD countries and conclude a positive relationship between TFP, employment share of large firms and proportion of large firms in the economy.

Bloom, Canning, & Sevilla (2002) model TFP using cross country panel data over a period of 1970-1990. They find that differences in TFP is a major reason for cross country differences in economic growth. Solimano & Soto (2005) find that dynamic Asian economies like Korea, Hong Kong, Thailand, and Singapore have had an impressive TFP growth rate (in comparison to other reference countries in their study). As a result, these countries have had a much steady progress in moving towards their steady state and have experienced much lower frequencies of growth crisis as compared to Latin America in the last 40 years. Turner, Tamura, & Mulholland (2013) in a cross-country analysis find that variation in TFP growth accounts for three-quarters of the variation in growth rates of output per worker across countries.

Sources of Productivity Growth in context of developing countries

Atkin et al. (2019) identify different sources of productivity growth in context of developing countries. These sources include improved entrepreneurship and ease of doing business, improved access to inputs along with reduction in factor misallocations, and supporting sectors that are a source of positive externalities.

Bloom, et al. (2013) in their famous study on India emphasize on the role of better management practices as a source of improving TFP. By providing free management consultation to the treated firms, they conclude that better management practices raised productivity by 17% as it led to quality improvements and reduced inefficiency. Moreover, within three years the treated firms were able to open more productive plants. Giorcelli (2019) examine the long-term impacts of introducing better management practices amongst firms. The study finds evidence of improvement in Italian firms’ performance for at least 15 years after they considered a US technical assistance program for workers. McKenzie & Woodruff (2014) find that business training programs help prospective owners launch their business more quickly.

Another important source of productivity gains for developing countries is the accumulation of better technology and inputs. Firms in developing countries enjoy the “advantages of backwardness” (Gerschenkron, 1961) as the technology has already been developed by the leading economies. Removing these barriers to technology can lead to productivity growth. Dalton et al. (2019) find that the introduction of better technology, i.e. an electronic payment system, increased the transparency of business dealings for merchants in Kenya. They design a field experiment where the e-payments help facilitate the promotion of SMEs. After sixteen months of this intervention, they find that the treated firms had improved access to financial opportunities and were more financially integrated.

Moreover, better availability of other factors of production also enhance productivity growth. Banerjee & Duflo (2014) study the impact of providing Indian firms with more credit under a policy reform. They conclude that many firms were credit constrained and that providing them with additional capital helped finance production. Moreover, the marginal return on capital was very high for the credit constraint firms. Similarly, availability of more inputs also enhances productivity. Topalova & Khandelwal (2011) show that as India moved towards trade liberalization, the reduction in input tariffs led to better availability of intermediate inputs and lead to an increase in firm level productivity. Goldberg et al. (2010) show that the availability of better intermediate inputs accounts for 31% of the new products introduced by the Indian firms and much of the expansion in product scope was due to availability of new input varieties rather than making the existing imported inputs cheaper.

Hsieh & Klenow (2009) use micro-level data to study misallocation amongst firms in India and China as compared to the US. They find that resource misallocation can lower TFP growth. Reallocation of capital and labor to equalize the marginal products in comparison to the US and can lead to a productivity gain of 30%-50% for China and 40%-60% for India. Moreover, factors like demand can help firms to grow. Ferraz et al. (2015) show that companies in Brazil who win a government procurement contract grow by at least 2.2% due to the increase in demand. Moreover, addressing various other market failures like information barriers can also help firms grow (Hausmann & Rodrik, 2002).

Trade and Productivity Linkage

The relationship between trade and productivity is a well-established in the literature. Trade impacts productivity and ultimately leads to economic growth through various channels. McCaig & Pavcnik (2018) study the bilateral trade agreement between the US and Vietnam under which large reductions were made in the US tariffs on the Vietnam exports. They find that because of the positive export shock there was a reallocation of labor from the informal sectors to the formal sectors in Vietnam, where this reallocation was greater for more internationally integrated sectors. There was an aggregate labor productivity gain as a result of this agreement which reduced worker heterogeneity and the differences amongst the labor intensity of production. There was an increase in efficiency as the large firms are more productive than the smaller, informal ones.

Reggiani & Shevtsova (2018) use Ukrainian manufacturing data from 2000-2006 to study the impact of export related productivity growth. They find that new exporters, particularly those associated with high technology sectors enjoy long term productivity growth as a result of opening to trade mainly due to learning through export. Moreover, Ahn et al. (2018) find that trade induces productivity gains via the input markets. A 1-percentage point reduction in input tariffs leads to a 2-percentage point increase in the TFP for a broad range of countries considered in the analysis. They also find that trade liberalization boosts foreign direct investment in the country leading to a higher growth. Halpern, Koren, & Szeidl (2015) attribute a quarter of the Hungarian productivity growth between 1993-2002 to imported inputs. According to their study, importing various varieties of inputs increased the firm’s revenue productivity by 22%. Bigsten et al. (2015) study the impact of both input and output tariff reductions on productivity gains for firms in Ethiopia. They do not find any evidence of output tariffs enhancing productivity while on the other hand input tariff reductions have large positive impact on productivity growth for firms. Hu & Liu (2014) find that with China's World Trade Organization entry, input tariff reductions increased productivity while output tariff reductions in fact had productivity depressing effects. Yu (2011) on the other hand find the opposite result. Considering the extent of each firm's involvement in trade and controlling for multiple sources of endogeneity for firms in China, the study concludes that output tariff reductions have a greater effect on productivity than input tariff reductions.

Kumar (2019) examines the impact of India's involvement in the South Asian Association for Regional Cooperation (SAARC). Analyzing data from 1990-2016, the study concludes that India's involvement in SAARC is also a source of productivity spillovers for Nepal, Sri Lanka, Bhutan, and Bangladesh. Bournakis et al. (2018) examine the impact of knowledge spillovers on output per worker as a result of opening up to trade. They show that knowledge-related spillovers are an important driver in promoting industry level output per worker. This gain is bigger for industries which use more intensive technology.

Theoretical Framework

In this subsection we highlight the themes considered in the dissertation regarding the trade-productivity linkage.

Measuring Productivity

The first part of this dissertation examines that impact of failing to account for measurement issues within the estimation of productivity. This is mainly because much of the work done on productivity lacks micro-level, disintegrated price-quantity data, and as a result, relies on total revenue data instead. Studies done in this context mostly use sectoral price deflators to back out output quantities and hence, use this to measure productivity. The reliability of results using this method has remained controversial, even though it is widely used in the 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 (Abott, 1991). 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. Klette & Griliches (1996) also argue that using deflated sales as a proxy for real output across firms can lead to biased results[2], particularly when the firms operate in an imperfectly competitive environment in which the prices are different across firms.

While the literature seems to support the idea that using sectoral deflators might lead to biased estimates of the production function, the main problem, even with studies attempting to correct for it is that even they lack the actual price-quantity data and hence

[2] They point out in their paper that when deflated sales are used as a proxy for firm's output using industry price deflators, the omitted price bias will be a part of the residual. This problem cannot be even solved with an instrumental variable (IV) since variables which are correlated with inputs or outputs (potential instruments) will always be correlated with this omitted price bias.

rely on the firm revenue instead. Klette & Griliches (1996) and Asker, Collard-Wexler, & De Loecker (2012)[3] use revenue data to develop alternate methods of measuring productivity rather than relying on basic sectoral deflators. While their methods do not solely rely on the sectoral deflator, such studies are still constrained by the limited data available. Measuring productivity by using the "revenue" approach as compared to an approach using actual "physical output" might lead to biased results. Foster, Haltiwanger, & Syverson (2008) show that revenue-based productivity is different than physical productivity, the main difference being the signs of their correlations with prices. While physical productivity is negatively correlated with prices, revenue productivity is positively correlated with prices. We can have more productive firms entering in the market who may be charging a lower price. In this situation, the revenue-based productivity might be understating their actual productivity since actual prices are not observed. How big could this data constraint be and whether inconsistency lies because of this data constraint is still an under-researched area.

Moreover, observing firm-level prices is itself important since prices might not just reflect changes in productivity but can also reflect demand shocks. According to Pozzi & Schivardi (2016), studies focusing narrowly on productivity might not measure the true productivity since the estimates derived might turn out to be a mix of productivity and demand shocks. If prices reflect market demand, then 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, something that cannot be done without observing prices.

Gaining market access through trade and its impact on firm productivity

While the positive relationship between trade and productivity is well-established, much of the work done in this context looks at the impact of firms lowering input tariffs and as a result gaining access to better and cheaper intermediate inputs which then help produce more output and enhances product quality. Olper et al. (2017) examine the impact of intermediate inputs in the food industry. They conclude that imported intermediate inputs play an integral part in the gains from trade. While import competition spurs firms' productivity, the impact of imported intermediate goods is much stronger than the impact of imported final goods. The import of newer inputs has also been extremely beneficial for firms in Italy. López (2006) used plant-level data from Chile and concluded that firms using imported intermediate inputs have a higher chance of survival. Sharma (2014) concludes that the impact of intermediate inputs on firms' output is of reasonable size while in fact the results of R&D are insignificant. Zhang (2017) find that using imported intermediate inputs improve the product quality and lead to productivity gains for firms in Colombia.

The other aspect of trade i.e., gaining market access due to lower output tariffs remains limited in the literature. Yu (2011) finds that for firms in China, a 10% reduction in output tariff leads to a 10% increase in firm productivity, which is much stronger than the impact

[3] Klette & Griliches (1996) show that adding the growth of the industry output in the production function can help solve for the productivity estimates despite the fact that prices are not observed. Asker, Collard-Wexler, & De Loecker (2012) combine the production function with the demand function to get a sales generating production function to help solve for the price bias.

of input tariff reductions. Linarello (2018) finds evidence that reduction in foreign tariffs leads to productivity gains by inducing firms to acquire more technology and to pay higher wages to skilled workers for firms in Chile. Given that there are relatively few studies in this area, the impact of gaining more market access in a fairly developed market on the productivity of firms in developing country remains limited. The impact of this market access on product quality remains even more limited. The second part of this dissertation focuses on this aspect of trade-productivity linkage.

Gaining market access through trade: sources of productivity gains

In this part of the dissertation, we contribute to the literature by focusing on how firm dynamics change in response to opening up to trade. Liu & Ma (2021) find that firms in response to output tariff reduction in China after its inclusion in the World Trade Organization (WTO) reduced their markups and markup dispersion. While on the other hand Wen (2021) focusing on the industry-level markup in China from 1999-2007 finding that markups have exhibited an upward trend and in fact trade liberalization has been a major factor in increasing China's aggregate manufacturing markups. Li & Miao (2018) find evidence that markups increase for firms in China as firms do not pass much of the cost reduction to customers by reducing prices as a result of trade liberalization.

Cai, Wu, & Zhang (2020) find evidence that firms in China gain economies of scale and learn about new technology. Trade liberalization increases the chances of product innovation and provides ideas to firms regarding upgrading and transformation. Bas & Paunov (2018), using firm-level data from Ecuador, find that trade liberalization gives firms a chance to expand their products, and in addition leads to the production of more skilled-based products. Lopresti (2016) on the other hand finds that firms in the US reduce their product diversification in response to the Canadian-US Free Trade Agreement (CUSFTA) of 1989.

Research Question(s)/Hypotheses

Chapter 1

In the first part of this dissertation, we focus on the measurement issues in productivity. We aim to answer the following questions:

1. How biased is the impact of a policy intervention (trade liberalization in our case) on firm productivity when there are measurement issues with the estimation of productivity itself? In other words, how different is the impact of trade liberalization on *measured* productivity as opposed to *actual* productivity?
2. What are the implications of not having detailed micro-level disaggregated output-price data and instead relying on sectoral deflators to deflate revenue data?
3. How does De Loecker's (2011) attempt to add in the demand system work to address the omitted price bias?
4. Is there a need to additionally control for demand shocks even if omitted price bias is not present?

Chapter 2

In this chapter we analyze the impact of the Free-Trade Agreement between Pakistan and China in 2006 to answer the following questions:

1. How has the increase in market access under the FTA impacted the productivity of textile firms in Pakistan?
2. How has the increase in market access under the FTA impacted the quality of textile firms in Pakistan?
3. How has the increase in market access under the FTA impacted the productivity and quality of textile firms in Pakistan based on their export status, especially the firms exporting to China?
4. Are there any productivity or quality spillovers from exporters to non-exporters located in close proximity?

Chapter 3

In this chapter we extend our analysis of chapter 2 and explore the sources of productivity gains for the textile firms in Punjab. We answer the following questions:

1. How do textile firms in Pakistan respond to the FTA by changing input usage, particularly capital investment?
2. How do textile firms in Pakistan respond to the FTA by changing their product scope and the number of segments they are active in?
3. How do textile firms in Pakistan change their markup, marginal cost, and price in response the FTA?
4. How do textile firms in Pakistan change their input usage, product scope and markups based on their export status, especially the firms exporting to China?

Methodology

Chapter 1

In this chapter, we estimate productivity using the methodology developed by De Loecker (2011). This methodology still relies on revenue data, but uses demand system (product and group dummies) and exogenous trade shocks to control for omitted price bias. In addition to this, we estimate demand shocks based on our disaggregated price-output data. This allows us to control for demand shocks in addition to controlling for omitted price bias. This helps us estimate actual productivity estimates net of demand and price variation.

Chapter 2

In this chapter we first estimate productivity based on the two major methods found in the literature i.e., by relying on production function invertibility and internal instruments. Firstly, we rely on production function invertibility using materials as a proxy for firm productivity based on the methodology developed by De Loecker, Goldberg, Khandelwal, and Pavcnik (2016). Secondly, we estimate firm-level productivity by relying on internal instruments as done under the System GMM, or panel method, using Blundell & Bond (1998, 2000, 2007) approach. We also extend this to add external instruments based on de Roux et al. (2020). Thirdly, we estimate productivity based on a new technique developed by Gandhi, Navarro, and Rivers (2020). Finally, we estimate product quality based on the methodology developed by Khandelwal (2010).

Chapter 3

We estimate markups and marginal cost based on the product-level estimates as in De Loecker, Goldberg, Khandelwal, and Pavcnik - DGKP (2016). We aggregate them to the firm-level by using revenue shares for each product. Alternatively, we also estimate firm-level markups and marginal cost based on the methodology by De Loecker & Warzynsksi (2012). To calculate the output elasticities to be used in this methodology we rely on the System GMM (Blundell & Bond, 2007) approach as well as the Gandhi, Navarro, and Rivers (2020) approach.

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1. Paper I: Measuring Actual TFP Growth: Stripping away Omitted Price Bias and Demand Shocks

I. Introduction

Given the importance of rising productivity for continued economic growth, a large part of literature has focused on the impact of various policy measures on productivity. What remains missing, however, is the essential question of how we accurately *measure* productivity since incorrect estimates of productivity may bias estimates of the impact of any policy. We study this question in light of the policy of opening up to trade in a developing country context and examine the consequences of not correcting for measurement issues in productivity.

One of the main reasons measuring productivity remains difficult is the relative unavailability of detailed micro-level data. Though more firm-level panel data sets have become available over time, they are restrictive for two main reasons: First, most only contain firm-level revenues rather than disaggregated output and price data. Second, even the revenue data that is available is aggregated at the firm-level rather than being product level.

Due to the unavailability of disaggregated data, most of the literature has used sectoral deflators to back out productivity estimates. Using sectoral deflators, however, has limitations, the major limitation being that not observing disaggregated output-price data leads to omitted price bias. Moreover, it will generate productivity estimates that contain price and demand variation. As a result, one obtains *measured* as opposed to *actual* productivity estimates. While the literature has generally accepted that the usage of sectoral deflators is flawed, the extent to which it leads to biased estimates remains unanswered.

Even the few attempts that have been made to study the problems associated with the use of sectoral deflators remain limited in their approach. This is mainly since because researchers have also relied on aggregated firm-level data. We add to the literature by attempting to examine the impact of not fully correcting for measurement issues in productivity.

We are able to measure physical productivity by using a detailed panel dataset of firms in Punjab, Pakistan. The data set contains disaggregated price and output data. Importantly, it is disaggregated not just at the firm level, but at the product level as well. Hence, we have firm, product, and time variation in our data set. Using this detailed data, this paper contributes to trade-productivity literature by measuring actual productivity after correcting for input simultaneity bias and omitted price bias, along with controlling for demand shocks estimated at the product-level. In other words, we are able to look at the impact of openness to trade on *actual* physical productivity rather than *measured* productivity, as had been previously done in the literature.

We also compare our results with those obtained using the methodology developed by De Loecker (2011). De Loecker looks at the impact of openness to trade on the productivity of Belgian firms and attempts to measure productivity as accurately as possible, though still relying on aggregated revenue data. He acknowledges 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). Using our disaggregated data, we show that the accuracy of the productivity results from the De Loecker's methodology is extremely sensitive to the accuracy of the sectoral deflators used, since the deflator fails to account for price variation both within and across firms.

We base our analysis around the Free Trade Agreement (FTA) between Pakistan and China in 2006, under which there were significant tariff reductions by both countries. In this study we focus our analysis of the productivity effects of the FTA on the textile industry in Punjab, Pakistan[4].

Our results indicate that only controlling for the input simultaneity bias (and not for the omitted price bias, as is commonly done in the literature) leads to upwardly biased results. Moreover, we find that is also essential to control for demand shocks. Firms are not only heterogeneous in productivity but also in how customers perceive the firm based on the quality of the product (including image, visibility of product,brand name, etc.) which is introduced via the demand side.

We begin by finding that a 10% reduction in tariffs increases firm productivity by 0.81% when we control for input simultaneity bias but fail to control for demand shocks. We then use De Loecker's methodology to control for demand shocks and find that this estimated impact falls by half. Finally, when we use our disaggregated data and control for both types of bias as well as for actual demand shocks, we find that the impact of a 10% reduction in tariffs on firm productivity falls to just 0.23%.

Overall, the total impact that tariff reductions under the FTA has had on productivity in the sector is 4.7% using the De Loecker methodology as compared to 7.8% when one fails to control for demand shocks. However, when we use disaggregated data to fully control for potential biases and demand shocks, the impact falls even further, to just 2.2%. 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; the reduction of tariffs has increased physical productivity by 16% in spinning.

The rest of the study is organized as follows. Section II describes the common types of biases found in the literature on productivity. Section III gives a review of empirical methodology. Section IV describes the precise measure of demand shocks based on disaggregated price and output data. Section V describes the Free Trade Agreement and section VI discusses our data sources. Our results are given in Section VII and Section VIII concludes.

[4] 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.

II. Common Types of Biases in the Productivity Literature

In this section, we discuss various types of biases found in the estimation of productivity. While input simultaneity bias and methodologies for correcting it have been well established in the literature, omitted price bias remains largely unaddressed due lack of disaggregated price and output data. We also discuss the new stream of literature emerging in the study of productivity which emphasizes the need to control for unobserved demand shocks. Even if we control for the input simultaneity bias, if omitted price bias and unobserved demand shocks go unaddressed (as it has in much of the literature), measured productivity estimates will differ from the actual productivity. We discuss these biases in more detail below.

The issue of input simultaneity bias dates back to the works of Marschak & Andrews (1944) who argue that a firm's decision regarding the usage of inputs depend on its own productivity, knowledge of which is often hidden to others. As a result, there will be serial correlation between productivity and input choice in time period *t*. The OLS, in this case, will fail to take this into account leading to an upward bias in the estimated input coefficients (Olley & Pakes, 1996)[5]. To correct for this, the two most popular methods in literature are the ones by Olley & Pakes (1996) and Levinsohn & Petrin (2003), abbreviated OP and LP hereafter. OP assumes that there is only one state variable, i.e., unobservable productivity, which causes differences in firms' investment behavior at a given point in time. Hence, they develop a semi-parametric productivity estimator where they use investment as a proxy for the firm's productivity. LP, on the other hand, show that 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 firms[6]. Both these methods are widely used in the productivity literature to correct for input simultaneity bias.

The omitted price bias, on the other hand, is something less able to be directly addressed in the literature, as it requires information on actual output and prices, which is available in few data sets. As a result, most studies rely on firm-level revenue and sectoral deflators to back out deflated output. While the usage of sectoral deflators has remained controversial, it is still widely used in the literature. Omitting actual prices can lead to measurement errors, particularly if real output is correlated with prices (Abbott, 1991). Klette & Griliches (1996) argue that using deflated output as a proxy for actual output can lead to biased results, particularly when the firms operate in an imperfectly competitive environment in which the prices vary across firms according to market power. Moreover,

[5] 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. 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 vairables and using lagged inputs as potential instruments. However, differencing variables means losing variation and intruments might only be weakly correlated with variables if they are differenced (Wooldridge, 2005).

[6] 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 investement 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.

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. To understand the omitted price bias, we start with a simple production function:

$$Q_{it} = A_{it} K_{it}^{\alpha K} L_{it}^{\alpha L} M_{it}^{\alpha M} \quad (1.1)$$

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 shares and A_{it} is the firm level productivity. Taking logs, we re-write the above equation as:

$$q_{it} = \beta_k k_{it} + \beta_l l_{it} + \beta_m m_{it} + a_{it} + u_{it} \quad (1.2)$$

where the lower case indicates that the variable is in log form. u_{it} is the unobserved error term. Since actual physical output is not observed in most of the datasets, the literature relies on deflating revenues to get (deflated) output in place of actual physical output, q_{it}. The log of deflated revenue is given as:

$$\widetilde{r_{it}} = p_{it} + q_{it} - \overline{p_{It}} \qquad (1.3)$$

where $\overline{p_{It}}$ is the log of sectoral deflator. Combining both the equations (1.2) and (1.3) gives us

$$\widetilde{r_{it}} = \beta_k k_{it} + \beta_l l_{it} + \beta_m m_{it} + (p_{it} - \overline{p_{It}}) + \Omega_{it} + u_{it} (1.4)$$

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:

$$E\big(x_{it}(p_{it} - \overline{p_{It}})\big) \neq 0 \text{ where } x_{it} = (k_{it}, l_{it}, m_{it})$$

Hence, there will be omitted price bias. True estimates of productivity therefore require controlling for this price difference. The problem is compounded for multi-product firms since firms produce heterogeneous products and charging the same price even for all products within the same firm itself leads to biased results, let alone charging the same price across firms. Thus, it is essential to have disaggregated price and output information to completely eliminate the omitted price bias.

De Loecker (2011), in his study on the impact of opening up to trade on the productivity of the Belgian firms, controls for the omitted price bias by introducing demand into the system. He estimates the demand system via the exogenous quota protections and product and group dummies as an attempt to get accurate productivity estimates, while still relying on firm level revenue and sectoral deflators. Thus, he attempts to use the demand shocks to control for the omitted price bias.

The more recent literature, however, focuses on controlling for demand shocks in addition to controlling for the input simultaneity bias and omitted price bias. In other words, even if actual output is observed demand shocks still need to be incorporated into the analysis. Controlling for demand shocks in addition to observing actual output is important for two main reasons (i) demand shocks are separate from productivity shocks (ii) demand shocks can be used to proxy to control for quality of the product.

Productivity and demand shocks are different not only in their causes but in how firms should respond to them. Productivity shocks represent a shift in production technology where businesses might need respond by reorganizing, adjusting capital and/or labor's skill mix (Pozzi & Schiardi, 2016). If firms are unable to implement these complementary innovations due to lack of expertise, they miss out on taking the full advantage of the productivity shock. This, however, may not be true for demand shocks. Under a demand shock, the need to accommodate a larger body of customers can simply be met by scaling up the production process without necessarily changing the organization's working. Less capable firms, who lack the expertise to reorganize and may be unable to adjust to productivity shocks, will not usually have the same problems in responding to demand shocks.

Pozzi & Schivardi (2016) in their study control for the demand shocks in addition to observing actual changes in physical output. They argue that firms are not only heterogeneous in productivity but also in how customers perceive the firm based on its image, visibility of product, brand name, marketing and customer relations etc., which all introduce heterogeneity amongst firms via the demand side. The literature has mostly ignored this aspect, since in order to separately identify demand and supply shocks, one needs to have information on actual prices.

Recent work by Atkin et al. (2019) identifies one of the shortcomings of the standard productivity measure, which is that it fails to adequately incorporate firm-level output quality into the analysis. They estimate a quality metric in their study on the flat weaving rug industry in Egypt. They argue that even if actual output is observed so that physical productivity is measured (eliminating omitted price bias), product specifications and quality measures vary significantly both across firms and within firms for different product lines. They conclude that in the absence of specification controls, physical output productivity is negatively correlated with quality productivity (whereby firms make lower quality rugs more quickly). In this case, physical productivity (TFPQ) is misleading and hence the revenue estimates of productivity (TFPR) may be a more suitable proxy for firm's capability. However, if these physical productivity measures are specification-adjusted, they have a tight correlation with firm capabilities. One way to control for these product specifications is by introducing demand into the analysis; thus Atkin et al. rely on the demand system to control for the quality index. Since demand shocks depend upon how consumers perceive the product with quality being an important determinant of customer perceptions, controlling for demand shocks automatically takes the quality concerns into account. Hence, controlling for demand shocks also addresses the issue of unobserved quality, an issue of growing concern in literature.

Empirical work confirms that firms respond differently to demand and productivity shocks. Carlsson et al. (2014) conclude that firms in Sweden respond more to demand shocks. They show that demand shocks, especially those which are permanent in nature, are the driving force behind job and worker reallocation rather than productivity shocks.

Foster, Haltiwanger, & Syverson (2008) study firms' survival based on the productivity and demand shocks faced. Results indicate that firms are more likely to exit due to low demand rather than low productivity (3 to 4 times larger impact). Hence, while both factors matter, demand variation 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 reflect market demand and, as a result, the link between productivity and growth might be overstated while the impact of demand side factors that matter for growth might be understated. Thus, it's essential to control for demand shocks in addition to controlling for input simultaneity bias and omitted price bias, which cannot be done until prices are observed.

III. Empirical Methodology

De Loecker's (2011) study is one of the few in the literature that attempts to control for the biases mentioned in the previous section, although he still relies on firm-level revenue data and, hence on, sectoral deflators. He looks at the impact of trade liberalization on the productivity of textile firms in Belgium. Despite his data constraints, he shows that even when relying on aggregated data, once an attempt is made to control for demand shocks and unobserved prices, trade liberalization leads to a 2 percent gain in productivity as compared to 8 percent as measured using standard techniques. De Loecker 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).*

De Loecker (2011) 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 the removal of quota protection to serve as an exogenous demand shock. He does this by introducing demand shifters, product and group controls and trade policy changes.

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

$$Q_{it} = K_{it}^{\alpha K} L_{it}^{\alpha L} M_{it}^{\alpha M} exp(\omega_{it} + u_{it}) \quad (1.5)$$

Where firm *i* produces output (Q_{it}) at time *t* using capital (K_{it}), labor (L_{it}) and materials (M_{it}). The α*'s* are the respective input shares for capital, labor, and materials. ω_{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 disaggregated data, he relies on sectoral deflators to back out deflated output.

To measure the response of actual productivity to trade liberalization, De Loecker introduces a constant elasticity of substitution (CES) demand system for firm *i*, where the elasticity of substitution is allowed to differ by segment, *s*.

$$Q_{it} = Q_{st}\left(\frac{P_{it}}{P_{st}}\right)^{\eta_s} exp(\xi_{it}) \qquad (1.6)$$

The demand system given in equation (1.6) 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 ξ_{it}. η_s is the elasticity of substitution which varies according to the segment, *s*.[7] Producers within the textile sector then face different demand elasticities based upon the textile segment(s) that they are active in.[8]

Since a firm's revenue is given as $R_{it} = Q_{it}P_{it}$, combining this with the expression of price from equation (1.6) and expressing in log form we get the sales generating production function as follows:

$$\widetilde{r_{it}} = \beta_l l_{it} + \beta_k k_{it} + \beta_m m_{it} + \beta_s q_{st} + \omega_{it}^* + \xi_{it}^* + u_{it} (1.7)$$

Where $\widetilde{r}_{it}$ is the deflated revenue given as ($\widetilde{r_{it}} = r_{it}$-$p_{st}$) where the lower-case letters represent logs of the variables[9].

The model above is further extended to allow for multiproduct firms. Since the input usage is not observed at the product level but rather at the firm level, De Locker's methodology assumes that input usage is directly proportional to the number of products being produced. Hence, to incorporate multiproduct firms, one just needs to control for the number of products being produced (np_{it}), where equation (1.7) can now be written as:

$$\widetilde{r_{it}} = \beta_{np} np_{it} + \beta_l l_{it} + \beta_k k_{it} + \beta_m m_{it} + \beta_s q_{st} + \omega_{it}^* + \xi_{it}^* + u_{it} (1.8)$$

The model can be further expanded by allowing for multi-segment firms. For this, the demand for each segment *s* in which the firm is active needs to be incorporated. This is done by simply expanding the term q_{st} to $\sum_{s=1}^{S} \beta_s \, s_{ist} q_{st}$, where a dummy variable s_{ist} takes the value 1 for firm *i* if it is active in segment *s* at time *t*. A firm can now face *S* different demand conditions depending upon the number of segments in which it produces,

[7] This implies a segment specific Lerner Index.

[8] 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 has been to estimate single markup and elasticity (Klette & Griliches (1996); Levinshon & Melitz (2006)).

[9] Note that the coefficients over here are given as β*'s* as opposed to α*'s* which are the reduced form parameters. The coefficient of interest over here β_h=$\left(\frac{\eta_{s+1}}{\eta_s}\right)\alpha_h$ where *h={l,m,k}*. For the segment specific demand parameter β_s=$\frac{1}{|\eta_s|}$. The returns to scale γ are obtained by summing up the production parameters, i.e., γ=α_l+α_k+ α_m. The unobserved productivity and demand parameters are given as ω_{it}^*=$\omega_{it}\left(\frac{\eta_s+1}{\eta_s}\right)$ and ξ_{it}^* =$\xi_{it}|\eta_s|^{-1}$.

which then helps identify segment-specific elasticities. Hence, to incorporate multi-segment firms, equation (1.8) can now be written as:

$$\widetilde{r_{it}} = \beta_{np} np_{it} + \beta_l l_{it} + \beta_k k_{it} + \beta_m m_{it} + \sum_{s=1}^{S} \beta_s \, s_{ist} q_{st} + \omega_{it}^* + \xi_{it}^* + u_{it} \quad (1.9)$$

We can now estimate equation (1.9) using the entire sample. It can account for single-product firms, single-segment-multiproduct firms, and multi-segment-multiproduct firms.

Under the CES demand system, the unobserved prices are picked up by the variation in inputs and demand per segment as represented by $\sum_{s=1}^{S} \beta_s \; s_{ist} q_{st}$. However, other factors may impact the prices and must be considered. Following Goldberg's (1995) strategy, De Loecker decomposes the unobserved firm-specific demand shocks (ξ_{it}) into three observable components and an unobservable shock. One potential candidate for the observable shock is a change in the level of trade protection, which can include quota restrictions or tariff rates; De Loecker uses the former while we use the latter, as shown by equation (1.10). The observable components are based on the products a firm produces, the sub-segments the firm is active in, along with the firm-specific tariff rate.

$$\xi_{it} = \xi_j + \xi_g + \tau tariff_{it} + \widetilde{\xi_{it}} \quad (1.10)$$

Where *j* refers to the product and g refers to the product group (sub-segment), while τ is the the impact of tariffs on the demand shock. $\widetilde{\xi_{it}}$ is the unobserved component of the demand shock (i.i.d). To illustrate this, ξ_j is a set of product-level dummies represented as $\sum_{j \in J(i)} \delta_j D_{ijt}$, while ξ_g is a set of sub-segment dummies represented as $\sum_{g \in G(i)} \delta_g D_{igt}$. Combining equation (1.9) and (1.10) we have the following equation (11):

$$\widetilde{r_{it}} = \beta_{np} np_{it} + \beta_l l_{it} + \beta_k k_{it} + \beta_m m_{it} + \sum_{s=1}^{S} \beta_s \, s_{ist} q_{st} + \sum_{j \in J(i)} \delta_j D_{ijt} + + \sum_{g \in G(i)} \delta_g D_{igt} + \tau Tariff_{it} + \omega_{it}^* + \epsilon_{it} \quad (1.11)$$

Where D_{ijt} are a set of dummy variables for products taking a value of 1 if firm *i* produces 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*.

Equation (1.11) is then taken to the data. It is worth nothing that now De Loecker accounted for the biases mentioned in section II. Omitted price bias and 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 that trade restrictions can impact demand and hence by controlling for them and (iii) finally including the demand per segment faced by firms i.e. $\sum_{s=1}^{S} \beta_s \; s_{ist} q_{st}$.

De Locker's methodology allows the trade shocks to impact the firm level residual demand instantaneously and hence, impact firm prices. The literature, however, has been a bit vague on how trade shocks impact the productivity process. The standard approach is based on the X-inefficiency idea where firms react to high competition by removing their inefficiencies where the aggregate productivity increases because of reallocation and exiting of the unproductive firms. De Loecker allows trade shocks to impact productivity with a lag. This is based on the idea that it takes time for firms to reorganize, change management, cut slack and adopt better practices as a result of trade shock which can lead to higher productivity. Hence, productivity changes as:

$$\omega_{it} = g_t(\omega_{it-1}, tariff_{it-1}) \quad (1.12)$$

Simultaneity bias is accounted for by using the LP approach using materials as to proxy for unobserved productivity. Hence the choice of materials m_{it} for a firm is directly related to the firm's productivity, capital stock as well as all the demand variables including trade protection (quotas in De Loecker (2011), tariffs in our case), segment dummies and product and group dummies:

$$m_{it} = m_t(k_{it}, \omega_{it}, tariff_{it}, q_{st}, D) \quad (1.13)$$

Where D here represents all the product and group dummies. Based on the function $h_t(.)$ productivity can be proxied as:

$$\omega_{it} = h_t(k_{it}, m_{it}, tariff_{it}, q_{st}, D) \quad (1.14)$$

Based on the standard LP approach, the coefficient for labor can be identifies in the first stage. The first stage can be expressed as:

$$\widetilde{r_{it}} = \beta_l l_{it} + \Phi_t(k_{it}, m_{it}, q_{st}, tariff_{it}, D) + \varepsilon_{it} \qquad (1.15)$$

The other parameters of interest are obtained in the second stage using the generalized methods of moments (GMM) with the following moment conditions:

$$E\left\{ v_{it+1}\,(\beta_m, \beta_k, \beta_s, \tau, \delta) \begin{pmatrix} m_{it} \\ k_{it+1} \\ q_{st} \\ tariff_{it+1} \\ D \end{pmatrix} \right\} = 0 \quad (1.16)$$

The demand parameter τ is identified by relying on the exogeneity of the trade shock and is hence identified by the moment condition $E(tariff_{it+1} v_{it+1}) = 0$. The β_s (demand parameters) are identified based on the moment conditions that the shocks to productivity aren't correlated with their lagged values (segment) output. The capital and material coefficients are identified using the standard moment conditions as used in the literature.

While the standard LP approach described above typically estimates the labor coefficient in the first stage and the other parameters in the second stage, in De Loecker's methodology it is difficult to assume that the labor can move independently from all other inputs, provided that the demand variation across firms is of great importance in the model. For this reason, finding a suitable data generating process is hard. A data generating process which can help identify is where the firm makes the choice of materials which is then followed by labor where both the input choices are made between the period t-1 and t with an optimization error term added to labor and not to materials. Doing this creates variation in labor choices which is linked to variation in output choices conditional on $m = (k, \omega, q_{st}, tariff, D)$. De Loecker's methodology relaxes the strong identification condition by simply not identifying the labor coefficient in the first stage but rather in the second stage. When using materials as a proxy for productivity, all the variables are collected in Φ(.) so the first stage is:

$$\widetilde{r_{it}} = \Phi_t(k_{it}, l_{it}, m_{it}, q_{st} tariff_{it}, D) + \varepsilon_{it} \qquad (1.17)$$

The only additional moment condition required to estimate labor coefficient is $E(v_{it+1} l_{it}) = 0$. Thus, the difference with the standard LP approach outlined above is that even the labor coefficient is identified in the second stage.

Finally, once the β's are estimated, the firm-level productivity is backed out. Using these estimates of productivity, one can then look at the impact of tariffs on firm level productivity as in equation (1.18).

$$\widehat{\omega_{it}} = \chi_0 + \chi_1 tariff_{it} + e_{it} \qquad (1.18)$$

IV. A More Precise Measure of Demand Shocks

Our work builds on the existing analysis in multiple ways. First, since we are able to observe disaggregated price-output data at the product level, we can completely eliminate omitted price bias as we do not have to rely on sectoral deflators. Hence, in our case the difference between firm-level and industry prices (p_{it} - $\bar{p}_{It}$) as shown in equation (1.4) is zero.

Secondly, as stressed by Foster et al. (2008) and Pozzi & Schivardi (2016), we control for demand shocks in addition to completely controlling for omitted price bias by relying on actual output and prices. While De Loecker uses demand shocks principally as a way to control for omitted price bias, Pozzi & Schivardi (2016) stress that demand shocks should be independently controlled for, even in the absence of omitted price bias.

Thirdly, we are better able to address the output quality concern raised by Atkin et al. (2019). This is mainly because while De Loecker controls for demand shocks by controlling for product and sub-segment dummies, we measure demand shocks more precisely. Our disaggregated data set also allows us to estimate demand shocks at the product level (explained in detail below). Estimating product-level demand shocks, rather than relying on dummies, is a better control of product specifications and hence, a better proxy of product quality. Therefore, our estimates of productivity are actual productivity estimates i.e., net of price and demand shocks.

Fourthly, 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, we observe the product mix of each firm for each year, and hence, we allow the product mix to change over time, adding more (and more accurate) variation to our analysis. Assuming that the product mix remains the same for around a decade is a strong assumption. Bernard et al. (2011) show that the firms in the United States do engage in product switching over time and hence change their product mix. De Loecker, himself, acknowledges that if firm-level productivity increases after trade liberalization and if, as a result, firms adjust their product mix accordingly, his analysis cannot take that into account due limitations of his data. He states that if that happens, his work *"cannot further separate the pure productivity effect from this product reallocation and selection dimension"* (De Loecker, 2011, page 1434). In fact, the product mix changes significantly in our sample over the decade covered[10], indicating that assuming a fixed mix over time is a very strong assumption to make[11].

Unlike De Loecker who decomposes the demand shock ξ_{it} into three observable components; namely, the product dummies, product-group (sub-segment) dummies and trade protection as in (1.10), we take a slightly more detailed approach. Using our unique disaggregated data at the product level ,we calculate 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 *j* at time *t*, using actual product-wise output and price information as shown in equation (1.19).

$$q_{jit} = \gamma_0 + \gamma_1 p_{jit} + \xi_{jit} \quad (1.19)$$

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 ξ_{jit} is the demand shock at the product level *j* faced by firm *i* at time *t*.

Applying equation (1.19) directly to the data is problematic since there might be a simultaneity bias as observed in a typical demand model like this one. To deal with this, we instrument for prices. We use tariff rates at the product level for all years as an instrument for prices, the main exogeneity argument being that tariffs can impact the prices charged by firms mainly due to global competition but a single firm on its own lacks the ability to influence the tariff rates. Hence, we instrument for prices using tariff rates as shown by equation (1.20):

$$p_{jit} = \theta_0 + \theta_1 \tau_{jt} + e_{jit} \qquad (1.20)$$

Where τ_{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:

$$q_{jit} = \gamma_0 + \gamma_1 \hat{p}_{jit} + \xi_{jit} \qquad (1.21)$$

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[10] Refer to section VI for more discussion on this.

[11] Since De Loecker does not observe the change in product mix for firms over time, he uses s_{is}, D_{ij} and D_{ig} i.e., if the firm *i* is active in segment *s*, the dummy variables for product *j* produced by firm *i* and the dummy variables of product group (sub-segment) *g* the firm *i* is active in and hence, controls for $\sum_{j\in J(i)} \delta_j D_{ij} + + \sum_{g\in G(i)} \delta_g D_{ig}$ where the product and product segment dummies do not vary with time (no *t* subscript) in equation (1.11). We allow these variables (product mix) to vary with time as well, hence, we use s_{ist}, D_{ijt} and D_{igt} in our analysis.

The residuals obtained from equation (1.21) can then be summed up at the firm level based on the revenue share a_{jit} of product *j* produced by firm *i* at time *t*:

$$\xi_{it} = \sum a_{jit}\, \xi_{jit} \qquad (1.22)$$

Once we have estimated these demand shocks, we can directly control for them instead of relying on the product and product group dummies *D* as under De Loecker's methodology. Hence equation (1.13) can be rewritten as

$$m_{it} = m_t(k_{it}, \omega_{it}, tariff_{it}, q_{st}, \xi_{it}) \quad (1.23)$$

since we now directly have estimates for ξ_{it}. It is worth noting that now rather than controlling for a large number of dummies (product and product group) we just control for one variable i.e., ξ_{it}. The moment conditions then become

$$E \left\{ v_{it+1}\,(\beta_m, \beta_l\,, \beta_k, \beta_s, \tau, \delta) \begin{pmatrix} m_{it} \\ l_{it} \\ k_{it+1} \\ tariff_{it+1} \\ \xi_{it} \end{pmatrix} \right\} = 0 \; (1.24)$$

With the parameters obtained by GMM, we estimate productivity and finally estimate the impact of tariffs on productivity as in equation (1.18). This will be the actual productivity estimate since this is measured using output, prices and demand shocks in the most disaggregated and precise manner in addition to controlling for the biases mentioned in section II.

V. Background of the Free Trade Agreement (FTA) between Pakistan and China

China and Pakistan began the process of lowering tariffs on each other's exports in the early 2000's and the process culminated in the signing of the Pakistan-China Free Trade Agreement (FTA) in 2006, which then led to further tariff reductions over a five-year period. As a result of this decade-long process, total trade between the two countries more than tripled and China became Pakistan's second largest import partner (Xin, et al., 2014). Negotiations for the second phase of the FTA began in 2013, with both parties proposing to reduce tariffs on approximately 90 percent of products[12]. Figure 1.1a shows that tariff rates declined over time for the textile sector's five segments[13] while Figure 1.1b shows how Chinese tariffs on textile imports from the ASEAN countries (which provided the greatest competition to Pakistani textile exports to China) also declined over this period. The most significant decline in Chinese tariffs on Pakistani textile exports occurred during the 2001-2005 period followed by smaller changes from 2005-2010. Also, while tariffs

[12] Detailed report on the FTA and the textile sector are available at: https://rdacell.com/Documents/Pakistan-ChinaFree.pdf
[13] We divide the textile sector into 5 segments: Spinning. Finishing, Clothing, Interior and Technical following the division done by De Loecker (2011).

fell across all categories, China's concessions to Pakistan were more substantial in the low-value added sectors like spinning and less generous in the higher-valued added clothing and garment sector. Figure 1.1b shows that China's tariffs on textiles coming from the ASEAN countries decreased along a similar trend as its tariffs on Pakistani textiles from 2001 to 2005, but then fell to near zero by 2010. By the end of the period we study, Pakistani exports were at a relative disadvantage in the Chinese market despite the FTA, especially in the higher value-added sectors.

Trade flows between Pakistan and China increased because of the lower tariffs, but Pakistan's imports from China rose at a much faster rate than its exports to China in spite of the concessions on textiles, worsening the trade imbalance precipitously (Figure 1.2). We can additionally see in Figure 1.3 that only the spinning segment saw a significant increase in exports. Chaudhry et al. (2017) examined some preliminary impacts of the Pakistan-China FTA on firms, finding that even where Pakistan gained more access to the Chinese market (as a result of China lowering its tariffs, in comparison to the sectors for which the tariff rates remained roughly the same), value added fell despite Pakistan's exports and employment rising in those sectors.

Figure 1.1a: China's Segment-wise Tariff Rates facing Pakistani Firms

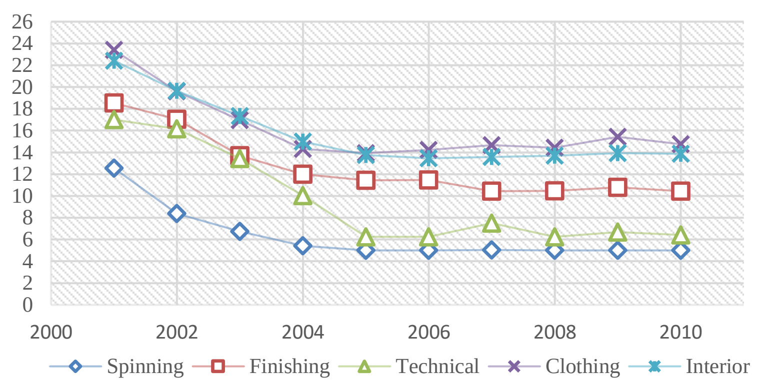
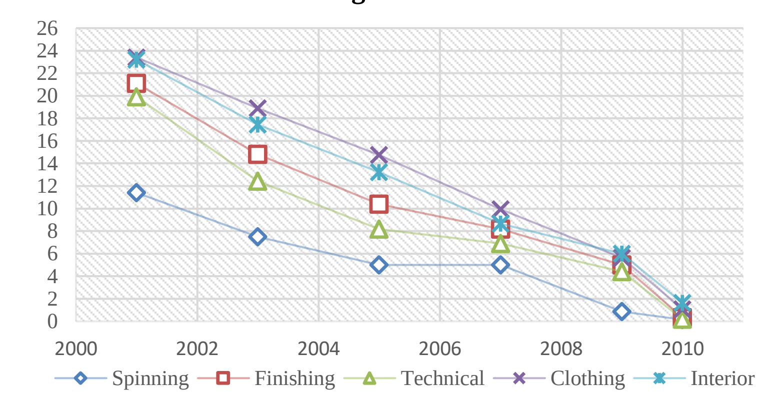


Figure 1.1b: China's Segment-wise Tariff Rates facing ASEAN Firms



Source: World Trade Organization (WTO) Tariff Analysis

Although benefitting from lower tariffs, at the same time firms in Pakistan were facing several challenges in the post-FTA environment, including a deteriorating law and order situation, which began with the assassination of former Prime Minister Benazir Bhutto in December 2007 while front runner to be re-elected, and a series of attacks on major targets including the Lahore High Court in 2009. In the same year, floods devastated southern Punjab, a major cotton growing region. That, along other weather events, contributed to a surge in cotton prices in 2010, raising the principal raw material costs for the textile sector substantially. Also, firms faced widespread electricity outages and 75 percent cited energy as a major constraint to growth in the World Bank Enterprise Survey (Bacon, 2019). Given the seemingly limited expansion in exports in the post-FTA period along with the other serious issues facing firms, our research examines what impacts, if any, the Pakistan-China FTA had on the Pakistani textile sector.

Figure 1.2: Trade Flows between Pakistan and China ($US Billions)

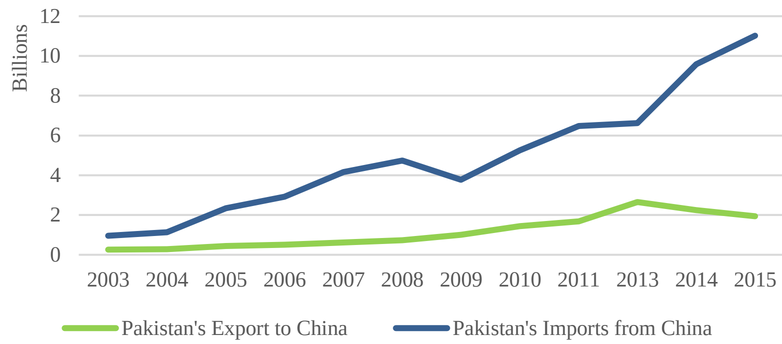
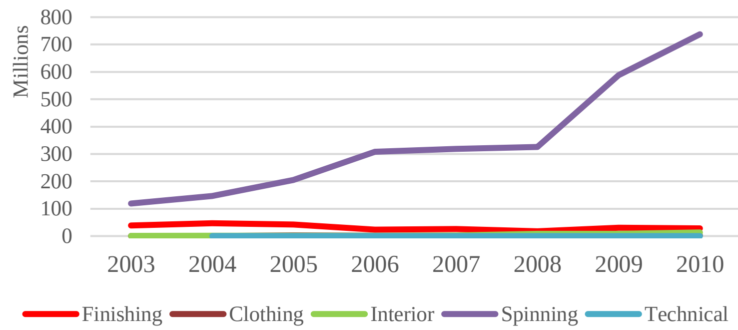


Figure 1.3: Pakistan's Segment Wise Exports to China ($US Millions)



Source: United Nations Comtrade Trade Data

VI. Data Sources

In this section, we detail the four main sources of data used in our analysis.

i. Census of Manufacturing Industries (CMI) Punjab, Pakistan

The main source of our firm-level data is the Census of Manufacturing Industries, or CMI. The CMI is a federal census of manufacturers in Pakistan that is administered every five years by the provincial statistical bureaus. It is a detailed survey containing information regarding the firm's revenues, input quantities and prices along with information on employment and labor costs, various capital stock measures, material inputs, and costs including energy and administrative costs. Using data from three waves of the CMI conducted in 2000, 2005 and 2010, we construct an unbalanced panel dataset for firms in the province of Punjab.

We limit our analysis to textiles, Pakistan's largest manufacturing and export sector. Following De Loecker's (2011) classification, we divide the textile sector into five segments: (i) finishing (ii) spinning, (iii) interior, (iv) clothing, and (v) technical[14]. Within each of these segments, there are product groups (called sub-segments) and then finally, within those product groups, are the individual products, which can each have a number of varieties.

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[15].

The main advantage of our dataset, as compared to most data used in the literature, is that it contains both price and physical output data at the product level, which helps us to deal with the omitted price bias that arises when relying on sectoral deflators. It also means that for every firm we also observe the product mix for each of these years.

In Table 1.1, we see that firms have transitioned from producing multiple varieties of a single product and producing in a single segment in the year 2000, to being multi-product but still primarily single segment in 2005 to being both multi-product and multi-segment firms in 2010. Over the same period, the number of different varieties of the same product per firm has fallen, from around 8 different varieties of the same product (and a maximum of 22 varieties produced by one firm in the data set) in 2000 to on average 3 varieties of a product in 2010.

[14] See appendix 1.1 for a broader classification of these segments.
[15] 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) classified in accordance with the HS code.

Table 1.1: Characteristics of Sample Firms from the CMI 2000-01, 2005-06, and 2010-11			
	Pre FTA		Post FTA
	2000	2005	2010
Multi-Segment firms	1.7%	5.70%	17.80%
Multi-Product firms	3%	22%	17%
Average number of varieties (differentiated products)	8	4	3
Total Number of firms	433	366	378

Source: Authors' calculations based on CMI Punjab 2000-01, 2005-06, 2010-11.

Table 1.2 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%. Therefore, assuming that the products produced, and consequently the segments the firms have been active in, is constant is a strong assumption to make.

Table 1.2: Segment Wise composition of firms (%)			
	Pre FTA		Post FTA
	2000	2005	2010
Spinning	59.53	48.99	36.47
Clothing	25.3	30.39	25.91
Interior	3.00	9.76	21.21
Technical	10.63	7.37	4.00
Finishing	5.40	9.21	26.50

Source: Authors' calculations based on CMI Punjab 2000-01, 2005-06, 2010-11.

ii. World Trade Organization (WTO) Tariff Data

We use the World Trade Organization (WTO) Tariff Analysis Online[16] to extract product-level tariff data from the Integrated Database (IDB). It contains information related to applied tariffs and country imports along with the Consolidated Tariff Schedules (CTS). This database contains details regarding members countries commitments on maximum tariffs with yearly information based on country and product-wise tariff rates[17].

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

$$tariff_{it} = \sum a_{jit}\ \tau_{jt} \qquad (1.25)$$

Where the tariff rate faced by firm *i* at time *t* ($tariff_{it}$) is an aggregation of the tariff rates imposed on product j at time t (τ_{jt}) produced by the firm. The tariff rates are added up after weighing the product-level tariff rates according to the revenue share of product *j* in

[16]Retrieved from the link: http://tariffanalysis.wto.org
[17] For each product, it reports the tariff line duties, average tariffs, principal suppliers, duty comparison, tariff concessions, tariff quotas, etc.

the production mix of the firm *i* at time t (a_{jit}). In equation (1.20) we directly use the product-level tariffs (τ_{jt}) to instrument for the product level prices p_{jit} for product *j* produced 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 data limitations holds these weights constant, which again is a strong assumption given our discussion of the evolution of textile firms in the product choice under the discussion of the CMI data[18].

Figure 1.1a in section V show the tariff rates over time for the five segments within the textile sector. Overall, we see a decline in the tariff rates imposed by China in all segments. It is worth noting that, although we present the *aggregate* trends in the tariff rate in Figure 1.1a, we use the more disaggregated product-wise tariff rates in the firm-level empirical analysis. It is this variation in the product-wise tariff rates that then provides variation in tariffs at the firm level 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.

iii. UN Comtrade Trade Data

We use the UN Comtrade Data by the United Nations to construct the total segment specific output. This is an International Trade Statistic Database containing over more than 3 billion data records for around 170 countries since 1962. It contains detailed trade statistics based by product categories and trading partners[19].

We look at the demand of the five segments in the Chinese market. Based on De Loecker's strategy, imports are also included to compute market size. Therefore, we consider the total demand in the Chinese market by considering both the total domestic production in China and total imports, that is:

$$Q_t = Q_t^{China} + Q_t^{Imports}$$

[18] 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 other wise 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.

[19] 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. Since the trade values available are in dollars, we convert them into Pakistani Rupees as our measurement of inputs are in rupees.

where $Q_t^{Imports}$ is directly available from the UN Comtrade Database. The main issue was with measuring 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}=$\mathbb{Q}_t Q_t^{China}$

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 $\mathbb{Q}_t$ to be the export to GDP ratio of China at time *t*. According to this, the amount China produces can be calculated as

$$Q_t^{China}=\mathbb{Q}_t^{-1} Q_t^{Export}$$

We can also get the data on Q_t^{Export} from the UN Comtrade Database[20]. This gives us our total textile and segment-wise outputs[21].

iv. All Pakistan Textile Mills Association (APTMA) Price Data

We use the price data available from the All Pakistan Textile Mills Association (APTMA) to construct the sectoral deflator. We use this data to deflate the revenues to obtain the deflated output to be used in our estimations using De Loecker's methodology. APTMA is the largest Pakistani national trade association of textile representing around 396 textile mills in the country. It compiles statistics and economic data on textile firms included details about its production levels, marketing trends, exports, among other details, and it also reports the unit value of various products including cotton yarn, cotton cloth and canvas, bags, towels, bed wear, garments, and others. Prices are available for the period 1995-2017. We calculate the Producer Price Index for the period 1996-2011 using this data with product weights based on the year 2010.[22]

Analyzing the PPI for the textile sector in Table 1.3 we see that the PPI falls from 1996-2000, fluctuates 2001-2008, rising again beginning in 2009. 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 went up, while our calculations show that PPI specifically for the textile sector remained depressed until 2009, as compared to the base year. This suggests a potential relationship between producer prices and tariff rate changes.

[20] Data on the export to GDP ratio is retrieved from : https://www.theglobaleconomy.com/China/Exports/

[21] It's worth nothing 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.

[22] 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 it into products which fall within the garment category.

Table 1.3: Producer Price Index (PPI)	
Year	Price Index
1996	100.00
1997	95.19
1998	83.79
1999	76.82
2000	71.28
2001	67.95
2002	71.62
2003	79.35
2004	80.50
2005	79.22
2006	83.86
2007	89.43
2008	84.96
2009	86.83
2010	116.22
2011	111.47

VII. Results and Discussion

In this section, we discuss the direction of the bias due the omitted price bias and simultaneity bias by comparing the coefficients of the estimated production function. We demonstrate how segment elasticities change once we control for demand shocks. We also test the empirical methodology based on De Loecker's approach in order to understand the extent to which missing disaggregated data can bias productivity estimates and the extent to which De Loecker's attempt to control for unobserved prices by accounting for demand shocks, while still relying on sectoral deflators, helps solve this problem. 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.

Column (1) of Table 1.4 presents 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. In column (3) we use the deflated output but we control for the simultaneity bias by using the LP method. Finally, in column (4) we attempt 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 aggregate demand faced in the textile sector along with using the actual output as the dependent variable.

Going from specification (1) to (2) corrects for the omitted price bias and hence, the downward bias in the input coefficients. Our coefficients in specification (2) go up for all 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 coefficents. Firms with high costs will charge higher prices and will as a result lose out on market share. These idiosyncratic changes in factor inputs suggest a negative relation between firms price and input usage, 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 require more input for productive firms; however when demand is elastic, output expansion tends to outpace productivity gains, implying the usage of more inputs, again suggesting a negative relationship between inputs and prices and a downward bias in the estimates.

Comparing specification (1) with (3), we control for the simultaneity bias. The omitted price bias is not, however, 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 the future at any given level of current productivity allowing it to continue operating, even at lower levels of productivity. By this self-selection, expectations of productivity will be decreasing the higher is capital, leading to a negative bias in the capital coefficient.

Table 1.4: Production Function Estimates

	OLS using deflated output	OLS using actual output	LP	LP with demand	
	(1)	(2)	(3)	(4)	
	β	β	β	β	α
Labor	0.082**	0.132**	0.069***	0.071**	0.138**
	(0.0285)	(0.0459)	(0.0113)	(0.0361)	
Materials	0.796***	0.840***	0.730***	0.740***	1.442***
	(0.0187)	(0.0216)	(0.0212)	(0.0071)	
Capital	0.068***	0.088**	0.100***	0.090***	0.175***
	(0.0136)	(0.0285)	(0.0141)	(0.0424)	
Output				0.442***	
				(0.0455)	
η				*-2.26*	

Bootstrap SE given in parenthesis. Results under (2) directly account for the omitted price bias by using actual output instead of deflated output. Results under (3) correct for simultaneity bias by using materials as proxy as suggested by Levinsohn and Petrin. The command used for this is levpet. Results under (4) also use materials as a proxy but control for aggregate textile output in order to incorporate the demand shock. Hence these estimates address both the omitted price bias and simultaneity bias.

We address both the biases in specification (4). We use the LP method to correct for simultaneity bias and control for aggregate demand of the textile industry (including imports) to control for demand and prices. We can see that since the directions of the omitted price bias and simultaneity bias work in opposition. Our results for specification

(4) are somewhat in-between our coefficients for specifications (2) and (3), which corrects for them individually[23].

ii. Price and Demand Effects: Measuring Segment Elasticity and Testing the Empirical Methodology

In this subsection we run the complete model and specifically focus on the elasticities of 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 as described in section III. We then compare the results with the estimates we get using actual physical output data instead, while still relying on De Loecker's approach. Finally, we compare the results under both specifications with the results we get using our data in the most disaggregated form i.e., using actual output and actual demand shocks as described in section IV.

Results are presented in table 1.5. Column (1) – (4) are based on De Loecker's method of using deflated output. De Loecker relies on product and product-group effects, including a firm-specific protection measure (quotas in his analysis; in our case tariffs) to control for unobserved demand shocks. It is interesting to note that the segments which are the most elastic in our case, that are interior and clothing, are also the most protected segments (refer back to figure 1.1a). 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 estimated 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 and are a proxy for the quality of the product. The industry's overall elasticity increases from -1.92 to -3.33 when we take the complete model into account. Controlling for 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 our exogenous trade protection measure. Moving from using deflated output to actual output eliminates the omitted price bias, since we do not have to rely on sectoral deflators. 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 (see column (2) in comparison with column (6)). This clearly

[23] Refer to foot note 9 for the discussion of how the *β's* are converted into *α's* for the specification under column 4.

indicates the presence of the uncorrected "omitted price bias" that is 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 β's fall and segment elasticities become more elastic. This is an essential finding in the sense that even if we have the actual output data but we still do not control for the demand shocks, we will still get estimates that are a mix of demand and productivity shocks. In order to measure the actual productivity, it is essential to control for 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 by 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. Prices also reflect market demand which is influenced by how consumers perceive the product, brand image, advertising etc. In this case, the common connection of productivity with firm growth might be overestimated and the impact of demand-side factors that matter for growth might be undervalued. Hence, disentangling the productivity and demand shocks is important. The results are also in line with the works of Atkin et al. (2019) who show the importance of controlling for product specifications in order to control for the product quality, which is done via controlling for the demand shocks. Hence, controlling for demand shocks is essential to back out actual productivity esitmates.

Finally, in the last two columns we present the results of measuring the actual demand shocks of firms at the product level by taking 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 explained in section IV. We believe these are the most accurate results since we use the data in its richest form. We use product-level tariff rates to instrument for prices[24]. Our results in table 1.5 for this specification show the most elastic demand as can be seen by column (9) and (10).

Much of the present literature evaluating the impact of trade or some 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. As we progress through the estimates of elasticity, starting from column (2) along through column (10), we are moving from estimates based on *measured* productivity, as typically done in literature, to estimates under *actual* productivity obtained by correcting for all the biases mentioned in section II and true demand shocks.

[24] Refer to appendix 1.2 for the results of equation (20) and (21).

It is 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. 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 into the productivity literature. It also specifies the importance of controlling for quality differences amongst firms.

Next, comparing the results using De Loecker's methodology of controlling for demand shocks with dummies in column (3) and (4), we can see that this method does improve the results since they are much closer to the actual coefficients presented under column (9) and (10) as compared to column (1) and (2). Hence our findings support 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 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 to column (7) and (8), where we correct for both the omitted price bias and demand shocks using dummies (following De Loecker) we get estimates which are in fact very close to the true estimates 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 better 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 would be the estimates be between column (3) - (4) and column (7) - (8). The only difference between these columns is the dependence on deflated output in the former and actual output in the latter, while both rely on De Loecker's method of controlling for demand shocks with dummies. 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 truest ones in column (9) and (10). Correcting for the price bias together with relying on De Loecker's method of demand shocks works extremely well.

So, if we control for demand shocks by relying on De Loecker's method, the main question is how accurate the sectoral deflator is. It is possible that a good deflator enables us to obtain estimates similar to the ones found when using the actual output levels. Therefore, it is critical to see how sensitive our estimates are to the use of the sectoral deflators.

Our data shows that using a sectoral deflator may be 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 1.4a-1.4d demonstrates the wide variation in product prices for the year 2005.

Figure 1.4a shows the price variation for women's shirts and blouses. Even within the same year, i.e., 2005, we observe significant dispersion in the prices for the same product. Prices for women's shirts and blouses are clearly not normally distributed, being as low as PKR 1000 to as high as above PKR 5000[25]. We can also see wide variation in the prices for other products as well including curtains and drapes, fabrics of nylon and carpets and other textile coverings[26]. Additionally, not only do we see significant dispersion in the prices for the same product for a given year, but 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. This seems to strongly imply that having the same deflator for both products will lead to biased results.

[25] 1 US $ equals to approximately around 150 Pakistani Rupee (PKR).
[26] 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 1.5: Segment Specific Demand Elasticities and Returns to Scale under different specifications

	Deflated Output				Actual Output				Actual Output and Actual Demand Shocks	
	Without Demand Dummies		With Demand Dummies		Without Demand Dummies		With Demand Dummies			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	β	Elasticity	β	Elasticity	B	Elasticity	β	Elasticity	β	Elasticity
Industry	0.52**	-1.92	0.30**	-3.33	0.49**	-2.04	0.22**	-4.54	0.18**	-5.55
Technical	0.74***	-1.35	0.64***	-1.56	0.72**	-1.39	0.59***	-1.69	0.55**	-1.82
Spinning	0.54**	-1.85	0.51**	-1.96	0.51***	-1.96	0.38***	-2.63	0.40**	-2.50
Clothing	0.53***	-1.88	0.46***	-2.17	0.33***	-3.03	0.26***	-3.84	0.25***	-4.00
Finishing	0.90***	-1.11	0.81***	-1.23	0.80***	-1.25	0.77***	-1.30	0.80**	-1.25
Interior	0.43**	-2.32	0.38**	-2.63	0.24***	-4.17	0.13**	-7.69	0.14**	-7.14
Inputs	β	α	β	α	B	α	β	α	β	α
Capital	0.09**	0.19	0.09***	0.13	0.10**	0.20	0.07**	0.10	0.09***	0.11
Labor	0.13**	0.27	0.20**	0.29	0.15**	0.29	0.17**	0.22	0.19**	0.23
Materials	0.58***	1.21	0.56***	0.80	0.46***	0.91	0.60***	0.77	0.59***	0.72
RTS		1.7		1.2		1.4		1.1		1.1

Figure 1.4a-1.4d: Product wise prices for the year 2005

Figure 1.4a

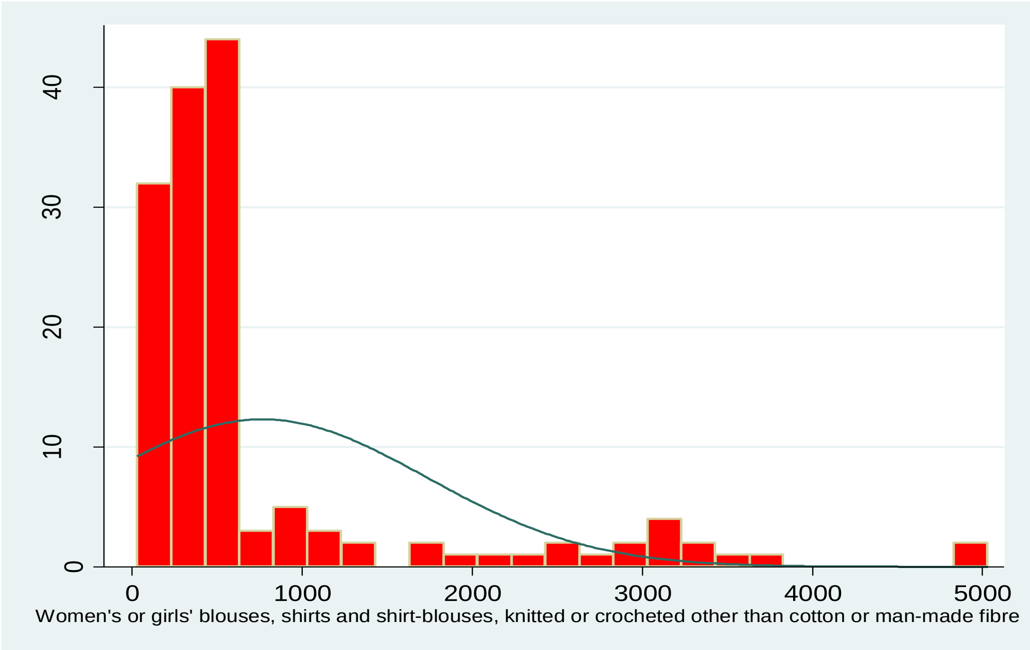


Figure 1.4b

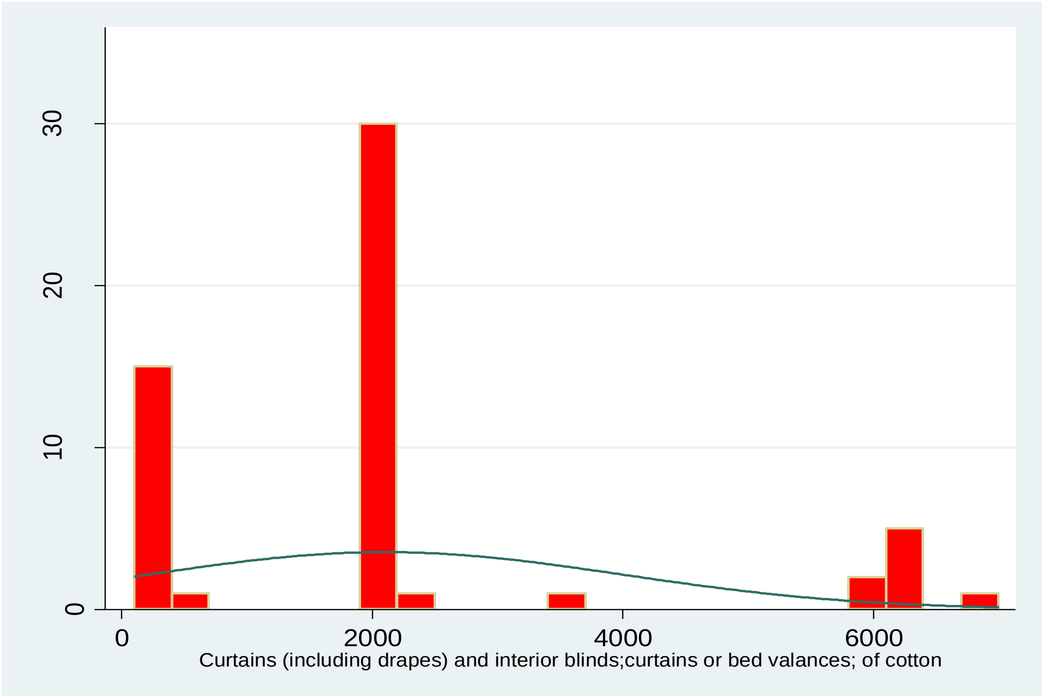


Figure 1.4c

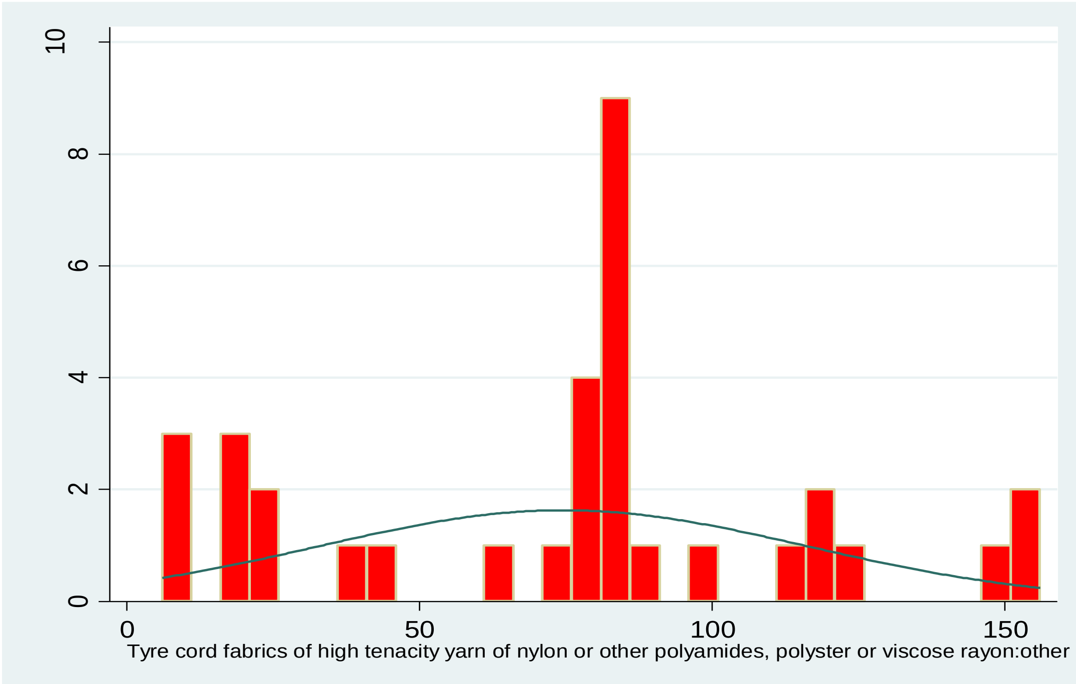
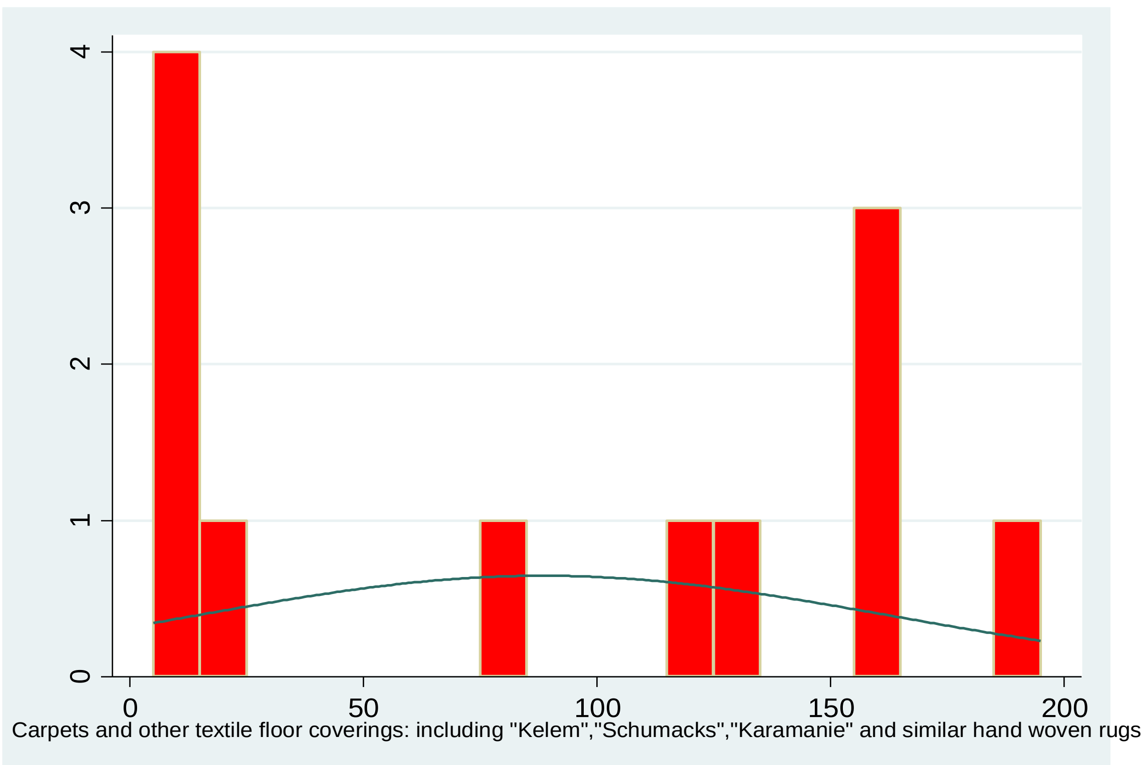


Figure 1.4d



iii. Impact of Tariff Changes on Aggregate Firm Productivity

This section shows the results from specification (1.18) under which we look at the impact of tariff changes on firm-level productivity.

Table 1.6 presents the results. As expected, we get a negative sign in all the specifications, indicating that high tariffs reduce firm-level productivity. We start with estimating productivity by taking equation (1.2) 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 demand shocks. Results show that a 10% reduction in tariffs increases firm's productivity by 3.35%.

In contrast, all of the other specifications control for simultaneity bias where we apply the LP 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/how we control for demand shocks.

In the specifications using deflated output, we test De Loecker's approach. Clearly controlling for demand shocks reduces the impact of tariff changes, where the impact of a 10% reduction in tariffs on firm-level productivity falls from 0.81% to 0.49%, once the demand shocks are controlled. This specifies the importance of incorporating demand shocks since the estimates of the impact is nearly halved.

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 firm productivity, where a 10% reduction in tariff improves productivity by only 0.33% as opposed to 0.54% when demand shocks are not 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 as described under section IV. If we fully control for the simultaneity bias, omitted price bias and true demand shocks, a 10% reduction in tariffs only increased firm-level productivity by a paltry 0.23%.

Clearly, we can see that controlling for demand shocks is important. Regardless of whether deflated revenues or actual output is used, applying De Loecker's method of using dummies to control for demand shocks causes the magnitude of the impact of tariff reductions to fall by nearly half. 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.

But getting better deflators is important. If we have actual output and we use De Loecker's method to control for demand shocks, we can get very close to the true effect of a tariff change; we get a coefficient of -0.033 per 1% change in tariffs using demand dummies on actual output which is the closest to the true impact of -0.023, using actual output and actual demand shocks. 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 impacts.

Table 1.6: Impact of Tariff on Productivity	
Specification	β
Deflated Output with OLS	-0.335*** (0.4383)
Deflated Output	
• Without Demand Dummies	-0.081*** (0.0099)
• With Demand Dummies	-0.049*** (0.0059)
Actual Output	
• Without Demand Dummies	-0.054*** (0.0043)
• With Demand Dummies	-0.033*** (0.0029)
Actual Demand Shocks	-0.023*** (0.0068)
Robust Standard Error in Parenthesis. *** Significant at 1%.	

iv. Impact of Tariff Changes on Segment-Wise Firm Level Productivity

In this sub-section, we look at the impact of tariff changes on firm-level productivity based on a segment analysis. Figure 1.3 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 1.1a.

Table 1.7 shows the results of the impact of tariff changes on firm-level productivity in a segment-wise analysis. We see a similar trend for all the segments under various specifications. 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. Based on the most precise estimates using actual output and actual demand shocks, 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 1.3, our results confirm that the impact of tariff reductions on firm productivity has been the most for the top two exporting segments to China, for which the tariffs are the lowest (refer to figure 1.1a).

Table 1.7: Impact of Tariff on Firm's Productivity-Segment Wise Analysis					
Specification	Segment				
	Spinning	Finishing	Interior	Clothing	Technical
	1	2	3	4	5
Deflated Output					
• Without Demand Dummies	-0.275*** (0.0092)	-0.217*** (0.0402)	-0.116*** (0.0148)	-0.197**** (0.0563)	0.078 (0.0534)
• With Demand Dummies	-0.220*** (0.0042)	-0.166*** (0.0160)	-0.071*** (0.0054)	-0.041*** (0.0062)	0.021 (0.0239)
Actual Output					
• Without Demand Dummies	-0.187*** (0.0063)	-0.152*** (0.0265)	-0.109*** (0.0300)	-0.145*** (0.0099)	0.063 (0.0575)
• With Demand Dummies	-0.183** (0.0848)	-0.141*** (0.0103)	-0.061*** (0.0219)	-0.036*** (0.0122)	0.017 (0.1124)
Actual Demand Shocks	-0.181*** (0.0052)	-0.113*** (0.0161)	-0.050*** (0.0047)	-0.037*** (0.0035)	0.0046 (0.0211)
Robust Standard Error in Parenthesis. *** Significant at 1%.					

v. The Net Impact of the 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 1.1a. Table 1.8 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 5%. The impact of the FTA using De Loecker's method reduces the impact of tariff reduction 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.

Comparing our estimates using De Loecker's approach while relying on deflated output versus the actual output, we can see that the impact falls further when we use actual output. However, even when using the actual output, we still must take demand shocks into account. Incorporating the demand shocks using De Loecker'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 output and actual demand shocks of 2%.

Table 1.8: Aggregate Impact of the FTA on Firm Level Productivity

Specification	Impact
• OLS	0.322
Deflated Output	
• Without Demand Dummies	0.078
• With Demand Dummies	0.047
Actual Output	
• Without Demand Dummies	0.052
• With Demand Dummies	0.032
Actual Demand Shocks	0.022

In table 1.9, 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, since it is the most precise. Our results are in line with those under table 1.7, where the biggest impact has been for the spinning segment.

Table 1.9: Aggregate Impact of the FTA on Firm Level Productivity

Segment	Impact
Spinning	0.167
Finishing	0.065
Clothing	0.017
Technical	-0.004
Interior	0.024

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

Reduction 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.

VIII. Conclusion

This study focuses on how to address the main measurement issues that arise when we evaluate the effects of trade policy on firm-level productivity. Though important, these issues have only partially been addressed in the literature mainly due to data limitations. Much of the firm-level data available is aggregate and consists of firm-level revenue. A common practice then has been to deflate the revenue with a sectoral deflator to back out firm-level output. Using deflated output has its limitations. Most importantly omitted price bias arises particularly when the price difference (that is, the difference between the actual price and sectoral deflator) is correlated with input usage. Moreover, not observing prices and actual output means that one cannot control for demand variations. Hence, what we get is *measured* as opposed to *actual* productivity.

Taking these measured productivity estimates, the literature then looks at the impact of various policy measures. But when one uses measured productivity, there is the possibility that the estimates of this impact may be biased. We show this by focusing on the Free Trade Agreement between Pakistan and China and estimating the impact of tariff reductions on the productivity of the textile sector in Punjab, Pakistan. We analyze the impact of tariff reductions on productivity using both measured and actual productivity estimates.

We are able to do this by overcoming the typical data constraints since we have a unique dataset which gives us disaggregated price and output information not only at the firm level but at the product level. This enables us to address the typical biases considered important in the productivity literature. Observing disaggregated data gives us the additional benefit of more precisely estimating the demand shocks, which are then controlled for in our estimates of productivity growth. These estimates are the actual productivity estimates as opposed to measured productivity estimates.

We then compare our results to those obtained under the methodology developed by De Loecker (2011) who controls for omitted price 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. The results support the use of De Loecker's methodology in cases where disaggregated data is missing, provided that we have accurate deflators which give us estimates of deflated output that are close to the actual output. Relying on weak deflators still yield biased results since they fail to take into account significant price dispersion both within and across firms. Our results also demonstrate that it is essential to incorporate demand shocks when considering the impact of any policy measure on productivity including trade. Demand shocks are essential to control for since they impact prices and are a proxy for quality differences amongst firms.

When we look at the impact of tariff reductions by China on Pakistani firms, we find that when we fully address both the omitted price bias and the input simultaneity bias along with incorporating the demand shocks, we obtain elasticity estimates that are larger than those obtained using the previous methodologies. The impact of a 10% reduction in tariffs on firm level productivity falls from 0.81% to 0.23% when we accurately measure productivity and control adequately for demand shocks. Also, the net impact of the entire FTA on firm level productivity drops from 7.8% to only 2.2% 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 correctly taken into account will researchers and policymakers be able to obtain accurate estimates of the impact of past and planned policy changes on firm productivity.

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2. Paper II: Measuring the TFP and product quality impact of the FTA: A analysis of the Pakistani firms gaining market access to China

I. Introduction

China has made a big push to expand its influence regionally (and beyond) through its Belt and Road Initiative (BRI). Formally launched in 2013, the more than $1 trillion portfolio of projects aim to augment China's connectivity both within Asia and outwards towards Africa and Europe by means of land and sea transport networks that encompass energy pipelines, railways, highways and ports (Chatzky & McBride, 2020). In Pakistan, China's investments pre-date the BRI, beginning with development of the deep-water Gwadar Port on the Arabia Sea that subsequently evolved into the China-Pakistan Economic Corridor, which includes a series of highways connecting China with Gwadar. At the same time, China has paired many of these investments with soft power initiatives such as offering greater access to its markets to countries including the ASEAN nations and Pakistan.

While much of the research on firms and trade considers the impacts when a country reduces its protection on imports[27], fewer consider the scenario where firms instead gain market access. The majority of studies that exist in the latter category study access gained through free trade agreements: Trefler (2004) on the Canada-US FTA, Iacovone & Javorcik (2010) on Mexico and NAFTA, Bustos (2011) on Argentina and Mercosur, and Yean and Yi (2014) on ASEAN and the ACFTA. Related experiences of newly gained market access are studied in Khandelwal et al. (2013) for China with the phasing out of the quotas that replaced the Multifibre Arrangement, De Loecker (2007, 2013) for Slovenia as it opened up in the 1990s after the fall of the Eastern Bloc and became an EU candidate, and Li (2018), Linarello (2018), and Garcia-Marin and Voigtländer (2019) for China and Chile, respectively, as they faced lower tariffs broadly on their exports. Also related are studies on episodes of exchange rate depreciations such as Wa (2008).

Our research is a case study in the second category and examines the extent to which reduced tariffs on the side of a major export market (China) can transform (or not) Pakistan's major export industry, textiles. In order to address issues raised in the recent literature regarding productivity estimations, we use three methodologies to estimate productivity: the De Loecker, Goldberg, Khandelwal, and Pavcnik (2016) methodology (hence DGKP), the Blundell and Bond (2000) System GMM methodology (hence System GMM) with and without external instruments (based on de Roux et al., 2021), and the Gandhi, Navarro, and Rivers (2020) methodology (hence GNR). Our results are especially relevant for developing countries that gain market access to larger, more developed economies as a result of bilateral or multilateral trade agreements.

Over the ten-year period that the Pakistan-China FTA[28] was implemented, the number of firms exporting to China changed only marginally and exports did not substantially rise except for in the

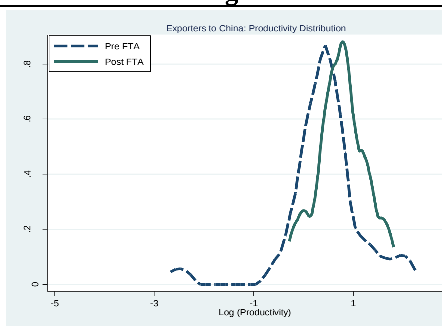
[27] These studies examine the pro-competitive effects (efficiency and reallocation, both between and within firms) of greater international competition on output and/or the benefits from being able to import higher quality inputs including greater variety, improved quality, and productivity: Amiti and Konings (2007), Bloom et al (2016), Brandt et al. (2017), Fan et al. (2018), Halpern et al. (2015), Pavcnik (2002), Topalova and Khandelwal (2011), Van Reenen (2011), Yu 2014.

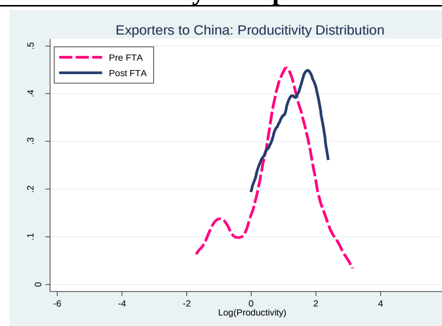
[28] We direct the reader to page 15 (paper 1, section V) of this document for detail about the about the Free Trade Agreement between Pakistan and China.

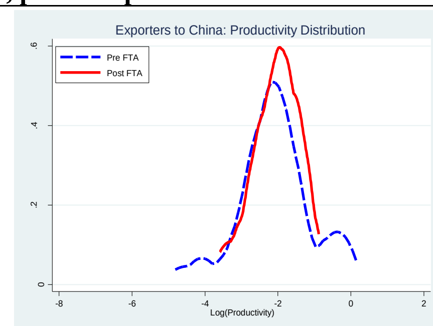
spinning sector. Even so, our results indicate that the productivity of textile manufacturers rose 3 to 8 percent and product quality rose 1-2 percent. Non-exporters' productivity and quality also rose, indicating the presence of spillovers. Testing this, we find that these spillovers occurred for non-exporters downstream from higher productivity exporters in close geographic proximity.

Figure 2.1 shows the distributions of productivity before (2000-05) and after (2010) the Pakistan-China Free Trade Agreement went into effect for exporters to China. The productivity distribution shifted rightward regardless of the methodology employed, indicating an increase in average productivity[29]. The figures for product-level distributions based on DGKP (2016) and quality distributions based on Khandelwal (2010) can be found in Appendix 2.1.

Figure 2.1: Distributions of Productivity of Exporters to China, pre- and post-FTA







DGKP (2016) methodology	System GMM methodology	GNR (2020) methodology

Source: Authors' Calculations based on CMI Punjab 2000-2001, 2005-06, 2010-11.

II. Literature Review

This study adds to the literature on the impact of export market opportunities on firms. In order to motivate our analysis, we begin by reviewing the literature on estimating firm-level productivity and then discuss the literature on productivity and exporting. Finally, we discuss the literature on firm-level spillovers.

Estimating Firm-level Productivity

Researchers have developed a range of methods to deal with the well-established simultaneity problem in firm productivity estimation, such that input decisions are correlated with total factor productivity that is unobserved to the researcher but known to the firm. This causes what is often referred to as "transmission bias" in an OLS estimation, so that the output elasticities of flexible (fixed) inputs are biased upward (downward). The earliest pioneering techniques, which used flexible inputs as proxy variables to identify production function parameters semi-parametrically (Levinsohn & Petrin, 2003; Olley & Pakes, 1996), were refined by Wooldridge (2009) and Ackerberg et al. (2015) to improve identification and efficiency. In addition, firm-level productivity estimation often suffers from problems arising from missing information on the prices of output and inputs, both of which tend to cause downward bias in the estimates of production

[29] Using DGKP's (2016) methodology, productivity appears to have risen for all firms, with the largest gains among the exporters to China and the smallest to non-exporters. Neither for exporters to other destinations nor non-exporters did productivity appreciable rise using either system GMM or GNR (2020).

function parameters when simple industry-level deflators are applied across firms (see De Loecker and Goldberg (2014) for a useful framework to disentangle the various issues)[30].

As this literature developed, researchers then began addressing the complexities introduced by multi-product firms. De Loecker (2011) attempted to deal with missing output price data in this context by introducing a demand system;[31] however, the model assumed a demand structure that may be difficult to justify in many environments. De Loecker, Goldberg, Khandelwal, and Pavcnik (2016; DGKP hereafter) develop a more flexible specification that they contend avoids overt assumptions on demand and market structure[32]. When physical output and product price data are separately available, as in the data we use, DGKP (2016) suggest estimating a physical quantity-based production function to avert output price bias. Further, under the assumption that the *physical* relation between inputs and output is the same for firms that manufacture the same product (be it single product or multi product firms), they use the data of single-product firms to understand input allocations at the product-level, rather than imposing that revenue shares proxy for input shares. In this framework, unobserved input prices are assumed to be a function of output quality and location, where output quality is estimated using Khandelwal (2010).

Even still, critics of these methods cite issues that remain unresolved, like the potential for input adjustment costs or market power to bias estimates, even when physical output data, arguably needed to estimate the correct output elasticities, is available (Bond et al., 2020)[33]. Further, most of these semi-parametric/proxy variable techniques have been developed for use on a *value-added* production function that differences out material inputs, whereas some recent work, including ours, uses gross output data so that the output elasticities of all inputs are estimated. This distinction is of particular importance when the output elasticity of materials, the only fully flexible input, are later used to calculate markups[34]. Specifically, DGKP (2016) estimate the output elasticity for a flexible input using moment conditions adapted from Ackerberg, Caves, and Frazer (2015), henceforth ACF, which had been developed for use on (typically price-deflated) value-added firm revenues. Ackerberg et al. (2007) had earlier criticized Olley-Pakes' identification of the output elasticity of labor, their fully flexible input (and proxy variable), due to multicollieарity and offered a solution where materials were substituted as the fully flexible input while labor became dynamic (or at least semi-predetermined) due to adjustment costs. Offering a related critique, Gandhi et al. (2020), hence GNR, argue that, absent an independent source of variation, the output elasticities

[30] A number of factors can be responsible for firm-level variation in prices of output or inputs once we move away from assumptions of homogeneous goods and perfect competition. Missing input prices make it difficult to control for output quality. Missing output prices are problematic because changes in firm revenues reflect a mixture of price and quantity changes, which often move in opposite directions, inhibiting efforts to disentangle the roles of technical efficiency and demand shocks in firm performance. This is because larger, more productive firms in imperfectly competitive markets (facing downward sloping demand) tend to charge lower prices (Foster et al, 2008; Hsieh and Klenow, 2009). In this environment, demand shocks, market power, and marginal cost shifters (due to changes in input price and/or quality) are all potential drivers of output price changes. Even simple changes in output quantities, when physical output data is available, can be difficult to interpret if we allow firms to vary quality over time.

[31] Segment dummies stood for demand shocks for Belgian textile firms exposed to a trade policy shock eliminating quotas, since changes in firm revenues reflect both price and quantity changes, and price changes often contain demand shocks.

[32] On the other hand, a working paper by Doraszelski & Jaumandreu (2021) suggests that the cost minimization problem in DLGKP (2016) does in fact rely on firm demand and bias will result in markup estimates unless we can "rule out any differences in demand across firms or time or assume that they can be fully controlled for by observables."

[33] The DGKP (2016) methodology addresses some issues highlighted by Bond et al. (2020) in that: (i) there are no assumption made regarding the market structure in this methodology, (ii) the methodology uses actual physical output and output prices, which eliminates the need for sectoral deflators as well as omitted price bias. Bond et al. (2020) also raise the issue of how the usage of inputs with the potential to alter demand can affect the accuracy of estimates, which is addressed to some extent by the fact that the DGKP methodology uses material inputs, which are less liable to be used to alter demand than labor.

[34] We would like to thank an anonymous reviewer for pointing this out. We discuss the markup estimation in detail in chapter III of this document.

are similarly not identified using ACF-type moment conditions applied to a gross output production function, but offer an alternative technique for estimating the output elasticity of materials through a transformation of the firm's first order condition.

The main alternatives to the proxy variable approaches described above belong to the class of dynamic panel methods that use internal instruments, so that lagged levels of inputs serve as instruments in a first differenced equation (Arellano and Bond, 1991). System GMM augments the basic first differenced equation with another in levels (using lagged differences in inputs as instruments), while also allowing for external instruments for inputs (Arellano and Bover, 1995; Blundell and Bond, 1998, Roodman, 2009). Relatedly, de Roux et al. (2021) use the same two equations as the system GMM but estimate them using a two-step procedure as well as instrumenting for labor with a function of the minimum wage.

In addition to GNR (2020), other alternatives to the proxy variable literature include Doraszelski & Jaumandreu (2013, 2018) who implement a parametric version of inversion along with firm-level wage and price data to estimate Cobb-Douglas and CES production functions respectively. Valmari (2016) relaxes the monotonicity (scalar observable) assumption in a multiproduct context that controls for input allocation across products. Dhyne et al. (2020) estimates the unobserved productivity terms for each firm-*product* while loosening the assumption used by DGKP that imposed the input-output relationship of single product firms on multiproduct manufacturers. Profit maximization conditions are utilized by Orr (2019) for input allocations in a multiproduct firm that also estimates quality.

Productivity and Exporting

One of the earliest insights of the productivity literature developed since firm-level data became available to researchers was that exporters tended to be significantly more productive than non-exporters (Bernard & Jensen, 1995, 1999). Economic theory suggested two competing sources of these differences: self-selection and learning-by-exporting.

The empirical literature has confirmed that exporters are fundamentally different and self-select into exporting, finding substantial differences in firm-level productivity between non-exporting firms and future exporters that precede their export entry (see the surveys in Wagner (2007, 2012); also Greenaway et al. (2007), Bernard et al. (2012); Clerides et al., (1998)). Learning-by-exporting on the other hand proposes that firm productivity increases as a consequence of exporting and to this effect, Bernard et. al (2006), De Loecker (2007, 2013), and Van Biesebroeck (2005) have found evidence that firm-level productivity can also increase subsequent to exporting[35].

An emerging literature lends support to the idea that there are dynamic complementarities between exporting, productivity, and investment or innovation activities so that they should be considered jointly (Aw et al, 2011; Bustos, 2011; Garcia-Marin & Voigtländer, 2019; Lileeva & Trefler, 2010; Linarello, 2018; Shen, 2016). Firms upgrade both in order to become exporters and as a result of exposure to export markets. Fieler et al. (2018) extend this framework further in modelling how

[35] Learning by exporting happens when, by facing foreign competition, firms accumulate a stock of (external) knowledge about technology, management practices, and foreign consumers' preferences, and by developing buyer-seller relationships.

firms jointly decide questions of exporting, scale, (output and input) quality, and skill intensity in an integrated framework.

Productivity Spillovers

Besides the direct effect of the free trade agreement on exporting firms, another important impact can occur through spillovers from exporters to non-exporters. Most of the literature having to do with productivity and quality spillovers relates to those arising from foreign direct investment (Aitken et al., 1997; Gorg & Greenaway, 2004; Girma et al., 2008; Javorcik, 2004; Waldkirch & Ofosu, 2010). A smaller literature explores locally generated spillovers. For instance, agglomeration spillovers by lowering costs can induce firms into export entry (Greenway & Kneller, 2008; Yang & He, 2014). But since we find very few instances of non-exporters becoming exporters after the implementation of the free trade agreement, we focus on other ways that productivity gains may accrue to non-exporters. Domestic exporters have been found to increase the productivity of non-exporters (Baltagi et al, 2015), often through backwards linkages with intermediate suppliers (Alvarez & Lopez, 2008; Linarello, 2018).

Our study will use the exogenous policy shock of reduced tariffs and export market opportunities induced by the Pakistan-China FTA to examine its impacts on the Pakistani textile sector. Specifically, we will measure the impacts of the tariff changes on the productivity and quality of firms, products, and segment differentiation. We also search for evidence of regional spillovers from exporters to non-exporters.

III. Data Sources

We use the Census of Manufacturing Industries (CMI) Punjab, World Trade Organization (WTO) Tariff Data and United Nations Comtrade Trade Data as described in paper 1 . We direct the reader to page 17, section VI for more detail on these data sets. Additionally, we use the Textile Export Transactions Database mentioned below:

Textile Export Transactions Database

We also utilize the textile export transaction database for Pakistan. This database contains detailed information on export shipments from Pakistan including the exporting firm’s name, export destination, date of shipment, and the value of the export transaction. We match this export data with the firms identified in the CMI to determine the export status of firms at each point in time. Table 2.1 below shows that the exporters are much bigger in terms of inputs than the non-exporters even pre-FTA.

Table 2.1: Characteristics of Sample Firms from the CMI 2000-01, 2005-06, and 2010-11			
	Pre FTA		Post FTA
	2000	2005	2010
Exporters	90	108	147
Capital (in PKR)[36]	362,839.7	506,279.1	654,147.8
Labor	445	456	475
Materials (in PKR)	364,714	413,322.5	1,410,323
Percentage of Exporters exporting to China	26%	21%	14%
Non-Exporters	343	258	231
Capital (in PKR)	217,970.6	276,705.1	325,221.8
Labor	161	252	266
Materials (in PKR)	155,007.7	180,341.3	193,269.3
Total Number of firms	433	366	378

Table 2.2 below shows the exporting status of the firms[37]. The total number of firms exporting after the FTA increased after the Pakistan-China FTA, but only two of the 31 new exporters were exporting to China. Of the firms exporting pre-FTA (to non-China destinations), 15 initiated exports to China after the agreement. Among the firms that continued exporting to China post-FTA, the share of their exports to China increased on average from 11 percent to 18 percent. Surprisingly, 12 firms exporting to China prior to the FTA stopped post-FTA, possibly due to the development that China's tariffs on products coming from the ASEAN nations fell below those offered to Pakistani firms after 2005.

Table 2.2: Characteristics of Pakistani Exporters in the Database of Export Shipment Transactions				
	Number Exporting Pre-FTA	Avg. Share of their Export Value to China	Number Exporting Post-FTA	Average Share of their Export Value Exported to China
Exporters (all destinations)	173		201	
Exporters to China	44	11%	49	14%
Continuing exporters to China (pre- and post-FTA)			32	18%
Exporters adding China (post-FTA)			15	6.7%
Export entrants to China (post-FTA)			2	5.2%
Exporters exiting China post-FTA			12	0%

Source: Authors' calculations based on the Database of Export Transactions from Pakistan, 2000-2010.

[36] 1PKR equals to approximately $0.006. The values reported in the table are at the current PKR value.
[37] Using the CMI dataset we were able to identify the names of more than 700 textile firms. Since CMI is an unbalanced panel, we were not able to identify all of these firms in all time periods. The export data set lists all exporters pre- and post-FTA. So even if we observe a firm in only one time period in the CMI (say post- FTA) we can still identify its export status in the pre-FTA period.

IV. Empirical Methodology: Measuring Productivity and Quality

In this section, we briefly discuss the methodologies used to measure firm level productivity and output quality for the subsequent analysis of the free trade agreement on the Pakistani textile sector. Our first set of results use the DGKP (2016) methodology to estimate firm-level productivity and Khandelwal (2010) to estimate product-level quality. We then implement the System GMM estimator for firm-level productivity (Blundell & Bond, 2000; de Roux et al., 2021). Finally, we employ the Gandhi et al. (2020) methodology to robustly identify the impact of the free trade agreement on firm level productivity. We discuss these methodologies in order below.

- ***De Loecker, Goldberg, Khandelwal, and Pavcnik -DGKP (2016)***

The nature of our data matches most closely with that used by DGKP (2016) since we also deal with multi-product firms and have access to price and physical output data. First, the DGKP methodology estimates a product-level (rather than firm-level) production function. Secondly, it avoids parametric assumptions on consumer demand, market structure, or the nature of competition (although Doraszelski & Jaumandreu (2021) argue that unobserved demand heterogeneity can still enter the firm's optimization problem). Third, their methodology aims to address a number of newer biases identified in the estimation of the production function, including *omitted input price bias* (due to quality-differentiated inputs used by firms) and the *unobserved allocation of inputs* within multi-product firms[38]. Finally, it incorporates estimates of product quality into the analysis. We discuss the methodology in detail below.

Theoretical Framework

Following the analysis of DGKP (2016) we have the production function for firm *f*. The firm produces product *j* at the time *t* can be expressed as:

$$Q_{fjt} = F_{jt}\left(V_{fjt}, K_{fjt}\right)\Omega_{ft} \qquad (2.1)$$

where *Q* is the physical output, *V* is a vector of variable inputs that are freely adjustable, *K* is the vector of fixed inputs which are assumed to have some adjustment cost, and Ω_{ft} is the firm-specific productivity. A firm produces a discrete number of products J_{ft}[39].We can take the log of the production function defined in (2.1) to obtain:

$$q_{fjt} = f_j\left(\chi_{fjt}\,;\,\beta\right) + \omega_{ft} + \varepsilon_{fjt} \qquad (2.2)$$

where q_{fjt} is the log of output and a function of χ_{fjt}, which is a vector physical inputs in log terms$\{V_{fjt}, K_{fjt}\}$, with β representing the respective input coefficients. Finally, let ω_{ft} be the log of productivity[40].

[38] Since input allocation across products is rarely observed, most studies make assumptions on how they are allocated. Foster et. al (2008) allocate input expenditure across products based on their revenue shares while De Loecker (2011) allocates the input share based on the number of products produced by the firm.

[39] Note that the production function *F(.)* is indexed by product *j*. This assumption implies that a single-product and a multi-product firm that produce the same product have the same production technology, although their productivity Ω_{ft} can differ.

[40] Like DGKP (2016), we do not have enough data to allow the production function coefficients to vary with time and thus assume that the coefficients remain constant. As a result, the *t* subscript is dropped in writing of the production function *f(.)*.

Writing equation (2.2) in terms of actual physical output helps alleviate omitted output price bias that could arise if we had constructed output using revenue data and by relying on sectoral deflators. However, two additional biases remain to be addressed. To understand them let $\widetilde{\chi_{ft}}$ be the vector of price index-deflated input expenditures. Hence the, product-level input quantities $\chi_{fjt}$for each input are then given by:

$$\chi_{fjt} = \rho_{fjt} + \widetilde{\chi_{ft}} - w^{x}_{fjt} \qquad (2.3)$$

where ρ_{fjt} is the fraction of firm input expenditures (in logs) associated to product *j* at time *t* and w^{x}_{fjt} is the deviation of the unobserved firm-specific input prices from the industry-wide input price index (in logs). Substituting this expression of physical inputs into equation (2.2) and denoting w_{fjt} as a vector of log firm product-specific input prices, DGKP (2016) obtain:

$$q_{fjt} = f_j\ (\widetilde{\chi_{ft}};\ \beta) + A(\rho_{fjt}, \widetilde{\chi_{ft}}, \beta) + B\big(w_{fjt}, \rho_{fjt}, \widetilde{\chi_{ft}}, \beta\big) + \ \omega_{ft} + \ \varepsilon_{fjt} \qquad (2.4)$$

Equation (2.4) has two additional unobserved terms as compared to equation (2.2): *A(.)* is referred to as the *input allocation bias* and arises due to the unobserved product-level input allocation ρ_{fjt} and *B(.)* is referred to as the *input price bias* that arises from unobserved firm-specific input prices w_{fjt}.

In the sub-sections that follow we discuss how the DGKP (2016) methodology solves for *omitted input price bias* (due to quality-differentiated inputs used by firms) and the *unobserved allocation of inputs* associated with the multi-product firms, since the typical firm-level dataset only records input expenditure data at the firm-level (as opposed to the product-level). We also discuss the moment conditions and the control functions used for identification.

Unobserved Input Allocation

DGKP (2016) assume that the firm's technology is product-specific and unrelated with the other products produced by firm *f*. This means that a single-product firm relies on the usage of the same technology as compared to a multi-product firm to produce the same product (though their productivity ω_{ft} can differ). They therefore rely on the single product firms to estimate the production function at the product level as in (2.4) without input allocation bias since, in the case of single product firms, the term *A(.)= 0* as ρ_{fjt}=1.

The main intuition behind this is that if the *physical* relation between inputs and outputs is the same for firms that manufacture the same product and the technology used to produce product *j* is independent of the other products manufactured by the firm, then the input-output relationship from single-product firms will approximate the input allocations for multi-product firms[41].

[41] This means that a single product firm will use the same technology and input allocation to manufacture a motorcycle as a multi-product firm that manufactures motorcycle and cars.

Without *A(.)*, equation (2.4) then can be written as[42]:

$$q_{ft} = f_j\ (\widetilde{\chi_{ft}};\ \beta)\ + B\left(w_{ft}, \widetilde{\chi_{ft}}, \beta\right) +\ \omega_{ft} +\ \varepsilon_{ft} \quad (2.5)$$

In the process of solving the problem of input allocation, this approach introduces potential selection bias, since a firm self-selects into being multi-product depending on its productivity and the availability of inputs. DGKP (2016) therefore implements a correction procedure that is based on the probability that a firm will be a multi-product firm given a productivity threshold and the firm's information set. We discuss more of this in a later section.

Unobserved Input Prices

Next, the DGKP (2016) methodology considers the omitted input price bias in *B(.)* in equation (2.4). In their framework, input prices can vary across firms due to different input prices across local input markets based on firm's location (G_f) and also due to differences in input quality (v_{ft})[43].

DGKP (2016) propose to account for the unobserved variation in input prices based on the observables, particularly the output prices. This is based on the intuition that output prices reflect input prices (i.e., producers of high value products have more usage of high value inputs as in Kugler & Verhoogen (2011)).

Product quality is defined as the mean utility a typical consumer will enjoy from consuming a product, net of its price. Hence, product quality can be expressed as a function of observable and unobservable product characteristics that impact the consumer utility, conditional on prices. The main idea being that when high quality inputs are complements, the prices of all the inputs faced by the firm can be expressed as a function of a single product "quality". Since the manufacture of higher quality output requires higher quality inputs, output prices reflect information regarding input prices. With input prices increasing monotonically in input quality, we can use output prices, market share, and also product dummies as a way to proxy for input prices[44].

We can write input prices w_{ft}^{x} as a function of output quality v_{ft} and firm location G_f:

$$w_{ft}^{x} =\ w_t\,(v_{ft}, G_f) \qquad (2.6)$$

where output quality v_{ft} is estimated based on the output price of the firm p_{ft}, a vector of market shares ms_{ft}, a vector of product dummies $D_{f,}$ and the export status of the firm, EXP_{ft}[45]. Hence equation (2.6) can be written as:

[42] Since this part of the estimation is based on single product firms, we remove the subscript *j*.
[43] This implies that two firms within the same industry can only face the same input prices if they are located in the same area and use the same input quality.
[44] An important assumption of the DGKP (2016) model is that the current input prices do not depend upon current input quantities (like in the case of bulk discounts). The model does not allow the input price faced by the firm to be a function of the size of the delivery. Though restrictive, this assumption is more general than the one used in most of the literature where firms face identical input prices. In contrast, DGKP (2016) allow input prices to differ across firms based on geographical location and/or quality differences.
[45] The export status of the firm is included to allow the market conditions in the foreign market to differ from those in the domestic market.

$$w_{ft}^{x} = w_t\,(p_{ft}, ms_{ft}, D_{f,}EXP_{ft}, G_f) \qquad (2.7)$$

Next the equation (2.7) is combined with (2.5) for the expression w_{ft}^{x} of $B\left(w_{ft}, \widetilde{\chi_{ft}}, \beta\right)$ to get:

$$B\left(w_{ft}, \widetilde{\chi_{ft}}, \beta\right) = B\left(\left(p_{ft}, ms_{ft}, D_{f,}EXP_{ft}, G_f\right) \mathrm{X}\, \widetilde{\chi c_{ft}}; \beta, \delta\right) \qquad (2.8)$$

$\widetilde{\chi c_{ft}}$ represents the fact that the *B(.)* function includes the input prices w_{ft} and their interaction with input expenditures $\widetilde{\chi_{ft}}$ hence $\widetilde{\chi c_{ft}} = \left\{1, \widetilde{\chi_{ft}}\right\}$. Therefore, the use of input control functions requires an additional parameter vector δ to be estimated along with the production function parameter vector β.

Unobserved Productivity and Selection Correction

The final source of bias that remains unaddressed in equation (2.5) is the unobserved firm productivity, ω_{ft}, which impacts firms' decision of input usage and potentially leads to simultaneity bias. The DGKP (2016) approach deals with this in two ways: (i) using a control function related to the statistic input demand function (ii) implementing a selection correction procedure as a result of relying on single product firms in order to estimate the parameters of the production function. We describe both in detail below.

The model relies on the materials demand function which is based on state variables including the number of products produced by the firm J_{ft}, the dynamic inputs for all products K_{ft}, productivity ω_{ft} and all additional variables which impact the demand for materials including firm location G_f, output prices p_{ft}, product dummies $D_{f,}$, market shares ms_{ft}, input prices $w_t(.)$, export status EXP_{ft} and output tariffs τ_{ft}. Hence the material demand function is:

$$\widetilde{m_{ft}} = m_t(\,\omega_{ft}, \widetilde{k_{ft}}, \widetilde{l_{ft}}, p_{ft}, ms_{ft}, D_{f,}EXP_{ft}, G_f, \tau_{ft}) \qquad (2.9)$$

All variables except for input expenditures and productivity are collected in the vector $z_{ft} = \left\{p_{ft}, ms_{ft}, D_{f,}EXP_{ft}, G_f, \tau_{ft}\right\}$. We can omit the number of products J_{ft} as this analysis is based on single product firms. Inverting (2.9) we get the control function for productivity:

$$\omega_{ft} = h_t\left(\widetilde{\chi_{ft}}, z_{ft}\right) \qquad (2.10)$$

In addition to the material demand control function, DGKP (2016) also control for the sample selection correction bias that arises by relying on single product firms only. Bias arises if a firm decides to add in another product or to ultimately become multi-product depending on its unobserved productivity and/or input use. This is corrected in two ways. Firstly, by relying on unbalanced panel data where firms at a given point in time are only single product. This includes firms which are at time *t* are single product but may eventually become multi-product in future. Like the DGKP (2016) dataset many firms in our analysis too start off as single-product and later introduce more products. Using the unbalanced panel helps to account for any selection concerns which may arise due to any non-random event which makes a firm multi-product based on its productivity ω_{ft}. Second, to correct for the sample selection bias, a sample selection correction procedure is applied which is based on the idea that the number of products manufactured by the firm is an increasing function of its productivity. If the firm crosses a certain productivity threshold, it can be classified as multi- product firm while firms below the productivity threshold remain single product firms and are included in the estimation. Hence, the probability of each firm remaining single product SP_{ft} is modelled on the productivity threshold which depends on state variables and on the firm's pervious period information set[46].

Productivity Process, Moment Conditions, and Identification

Vectors β and δ are estimated by DGKP (2016)based on the moment conditions related to the productivity shock innovation ξ_{ft}. The law of motion for productivity is given as[47]:

$$\omega_{ft} = g_t\left(\omega_{ft-1}, EXP_{ft-1}, \tau_{ft-1}, SP_{ft}\right) + \xi_{ft} \quad (2.11)$$

To estimate equation (2.11), the input correction from equation (2.8) and unobserved productivity from equation (2.10) is plugged in to get:

$$q_{ft} = \phi_t\left(\widetilde{\chi_{ft}}, z_{ft}\right) + \varepsilon_{ft} \qquad (2.12)$$

Where $z_{ft} = \left\{p_{ft}, ms_{ft}, D_{f,} EXP_{ft}, G_f, \tau_{ft}\right\}$ and $\phi_t(.) = f_j\ (\widetilde{\chi_{ft}};\ \beta)\ + B\left(w_{ft}, \widetilde{\chi_{ft}}, \beta\right) + \ \omega_{ft}$. The output noise is represented by ε_{ft}.

While the variables proxying for input prices (2.7) also enter in the input demand function (2.10), they do not affect the identification of the parameters of the production function. The sole aim of the first stage estimation is to get predicted output $\widehat{\phi_{ft}}$[48]. After estimating the predicted output $\widehat{\phi_{ft}}$ from the first stage[49] and using equations (2.5), (2.8) and (2.12), unobserved productivity ω_{ft} can be estimated as:

$$\omega_{ft}(\beta, \delta) = \widehat{\phi_{ft}} - f_j\ (\widetilde{\chi_{ft}};\ \beta) - B\left(\left(p_{ft}, ms_{ft}, D_{f,} EXP_{ft}, G_f\right) \mathrm{X}\ \widetilde{\chi c_{ft}}; \delta\right) \quad (2.13)$$

Where $B(.)$ is the price control function[50]. To estimate the vectors β and δ, moment conditions are formed based on the productivity shock ξ_{ft} in (2.11). Using equation (2.13), ω_{ft} is projected on the elements of $g(.)$ to get ξ_{ft} as a function of $\xi_{ft}(\beta, \delta)$:

$$\xi_{ft}(\beta, \delta) = \omega_{ft}(\beta, \delta) - E(\omega_{ft}(\beta, \delta) |\ \omega_{ft-1}(\beta, \delta), \tau_{ft-1}, EXP_{ft-1}, SP_{ft}) \quad (2.14)$$

Therefore, the moment conditions to identify the parameters are given as:

[46] DGKP (2016) assume that the decision to become a multi-product firm is made in the previous period.

[47] In the DGKP (2016) approach, the tariff variable and export status dummy variable are included in the law of motion to allow for the possibility that they may have an impact on productivity. However, including them does not mean that they will have an impact. Therefore, including these variables does not mean a particular result of the effect of tariffs and export status on productivity.

[48] E.g., the output prices in the first stage control for both the input quality and unobserved productivity but there is no need to distinguish the impact when we estimate the predicted output.

[49] $\phi_t(.)$ is estimated at the third-degree polynomial in all its elements (except for product dummies).

[50] *B(.)* is approximated using a flexible third order polynomial.

$$E(\xi_{ft}(\beta,\delta)Y_{ft})=0 \qquad (2.15)$$

where Y_{ft} includes lagged materials along with current labor and capital, their higher order terms, and interaction terms, lagged output prices, lagged market shares, lagged tariffs, and their interactions with the inputs. Using these, the coefficients of the production function are identified depending on the assumption that the current shocks in productivity will lead firms to adjust its material choice while on the other hand labor and capital may not react immediately to such shocks (they can differ both across firms and time)[51]. Additional moment conditions[52] with the other elements in Y_{ft} are used to identify jointly the production function coefficient β and the input price variation coefficients δ. Finally, the production function is estimated using a GMM estimation procedure[53].

Control functions for input prices and timing assumptions

Here we briefly summarize the input price control function, law of motion assumed for the productivity along with the timing assumptions which help the coefficients to be estimated. As mentioned earlier, the identification strategy is based on two control functions in order to estimate two unobservable: input prices and the firm productivity.

$$w_{ft} = w_t\,(p_{ft}, ms_{ft}, D_{f,}EXP_{ft}, G_f) \quad (2.16)$$

$$\omega_{ft} = g\big(\omega_{ft-1}, EXP_{ft-1}, \tau_{ft-1}, SP_{ft}\big) + \xi_{ft} \quad (2.17)$$

Unobserved productivity ω_{ft} enters the equation (2.5) linearly, while the input prices w_{ft} enter non-linearly as a part of the term *B(.).* After substituting the input price control function into the expression for unobserved productivity, DGKP (2016) get equation (2.8). It is worth noting that the input price control function is used in the first stage to remove the noise from the data. In this stage, materials are used as a proxy for productivity and given that material demand depends upon input prices, it is essential to control for input prices above. However, in the first stage the coefficients of the production function are not identified. Its sole aim is to remove the noise Ɛ from the data.

Moreover, if we consider the production function coefficients β and the coefficients associated with the input price correction term δ, these are identified off the timing assumptions. DGKP (2016) assume materials are freely adjustable inputs and as a result are correlated with contemporaneous productivity. Likewise, current output prices are correlated with current productivity. In contrast to this, capital and labor are both dynamic inputs and hence are

[51] DGKP (2016) assume that firms adjust materials freely while labor and capital are dynamic inputs which face adjustment cost. For that reason, lagged materials are used in the moment conditions.
[52] E.g., the moment condition to identify the parameters with output price are identified using the moment condition E($\xi_t p_{t-1}$)=0 which is based on the idea that current output prices do react the productivity shocks, so lagged output prices need to be used instead to account for the serial correlation in prices.
[53] DGKP (2016) adopt a trans-log functional form for *f* in equation (2.5) mainly because it allows output elasticities to change over time and across firms (although the production function coefficients are constrained to be the same). Finally, DGKP (2016) use firms in the model which manufacture a single product in at least 3 consecutive time periods. For our analysis, we restrict it to at least 2 consecutive time periods given a smaller sample size.

uncorrelated with productivity innovation ξ_{ft}. Using these assumptions, the moment conditions are formed.

In addition to this, two more identification issued are important here. Firstly, since the *B(.)* term incorporates the input expenditures $\widetilde{\chi_{ft}}$, this raises the concern about the identification of the production function coefficients β . They are identified, since although the $\widetilde{\chi_{ft}}$ enters the input price term *B(.)* but only through its interaction with input prices[54]. Secondly, some observables enter both the law of motion for unobserved productivity and input price control function e.g., the export status of the firm. The coefficients for such variables are again identified given the off timing assumption. The export dummy enters the law of motion for productivity in *t-1*, while it enters the input control function for the current time period *t*. The main assumption here is that productivity reacts to changes in firm's environment with a lag since firms take some time to adjust their efficiency (improve management practices, hire better mangers, etc.) while output and input prices may respond immediately to changes in the economic environment. As mentioned earlier, since these variables enter the input price control function with their current values, they are correlated with ξ_{ft} since by assumption they respond to contemporaneous environment shocks which creates the identification problem. For this reason, the moment conditions are based on the lagged values of these (not the current values) as mentioned in equation (2.15) where Y_{ft} contains the lagged values of output prices, market shares etc.

Recovering Input Allocations

To estimate the product *j's* input share ρ_{fjt} for multiproduct firms, q_{fjt} is projected on the same variables earlier as in the first stage such that $\widehat{q_{fjt}} \equiv E\left(q_{fjt} \middle| \emptyset_t\left(\widetilde{\chi_{ft}}, z_{ft}\right)\right)$. Given that the productivity is firm-specific and log additive and given that inputs are divisible across products, the production function can be rewritten as: $\widehat{q_{fjt}} = f\left(\widetilde{\chi_{ft}}, \widehat{\beta},\ \widehat{w_{fjt}}, \rho_{fjt}\right) + \ \omega_{ft}$ and can be recovered $\left\{\left\{\rho_{fjt}\right\}_{j=1}^{J}, \omega_{ft}\right\}$ using:

$$\widehat{q_{fjt}} - f_1\left(\widetilde{\chi_{ft}}, \widehat{\beta},\ \widehat{w_{fjt}}\right) = f_2\left(\widetilde{\chi_{ft}}, \widehat{w_{fjt}},\ \rho_{fjt}\right) + \omega_{ft} \qquad (2.18)$$

$$\sum_j exp(\rho_{fjt}) = 1 \qquad (2.19)$$

To recover the input allocation across multi-product firms, the production function is separated into two components where f_1 does not depend upon ρ_{fjt} while f_2 has all the terms with it. The input prices $\widehat{w_{fjt}}$ are based on the input price function as in (2.7). Since input allocation sums up to 1 as in (2.19) across multi-product firms, a system of $J_{ft} + 1$ equations for each multi-product firm (where J_{ft} is the number of products produced by firm *f* in time *t)* is solved to recover input allocations.

[54] We direct the reader towards Appendix B in DGKP (2016) for a detailed discussion on this.

- ***Khandelwal (2010)***

This section describes how we estimate output quality of products using the methodology by Khandelwal (2010) which uses a nested logit demand system that allows for preferences of both horizontal and vertical attributes. Quality is a vertical attribute of the model which captures the mean value a consumer attaches to the product. It is equally important to incorporate horizontal product differences since expensive imports may coexist in a market with cheaper rivals, where price might not be an appropriate proxy for quality.

Consumer *n*'s preferences are modeled by assuming that she purchases that variety of the product *ch,* within product *h,* at time *t,* that gives the highest utility. Thus, demand can be represented as:

$$ln\ (s_{cht}) - ln\ (s_{ot}) = \lambda_{1,ch} + \lambda_{2,t} + \alpha p_{cht} + \sigma ln\ (ns_{cht}) + \lambda_{3,cht} \qquad (2.20)$$

where $\ln(s_{cht})$ is the log of variety *ch's* overall market share and ns_{cht} is its market share within product *h* (nest share). Ln (s_{ot}) is the log of the outside option's market share and p_{cht} is the price of the variety *ch* at time *t*. Quality is defined as $\lambda_{1,ch} + \lambda_{2,t} + \lambda_{3,cht}$, reflecting a valuation of variety *ch* that is common across consumers[55]. The quality term is decomposed into three main elements: $\lambda_{1,ch}$, the time invariant valuations that the consumer attaches to variety *ch* reflecting variety fixed-effects; $\lambda_{2,t}$, capturing time trends across all varieties represented by the time fixed-effects; and $\lambda_{3,cht}$, a variety-time deviation observed by the consumer (and not by the econometrician) that plays the role of estimation error.
The quality of variety *ch* is then computed as[56]:

$$\lambda_{cht} = \hat{\lambda}_{1,ch} + \hat{\lambda}_{2,t} + \hat{\lambda}_{3,cht} \qquad (2.21)$$

- ***System GMM, or Panel Methods, using Blundell & Bond (1998, 2000, 2007) and de Roux et al. (2020)***

Panel data methods, when applied to the estimation of production functions, implement Generalized Method of Moments (GMM) estimation using predetermined variables in the estimation of a linear dynamic model. The standard estimator (Difference GMM) is based on a first differenced equation using the available lags of predetermined inputs as (internal) instruments. However, Mairesse & Hall (1996) argued that such estimates might produce unsatisfactory results. Elaborating on this, Blundell & Bond (1999) suggest that just using lagged *levels* of instruments might give rise to a "weak instruments" problem due to weak correlations between the first differenced variables and their lagged levels. The poor performance of this standard GMM estimator can cause a large finite sample bias and poor precision in the estimator. For these reasons, Arellano and Bover (1995) proposed the extended GMM estimator (also known as System GMM), which considers additional orthogonality conditions, and includes an equation in levels with lagged *differences* of inputs as (internal) instruments in addition to the standard differenced equation instrumented by lagged levels of inputs. In addition, external instruments for inputs can also be included (Roodman, 2009).

[55] Note there is no subscript *n* in these terms since it represents common valuation across all consumers.
[56] We aggregate the quality at the firm level by using product revenue weights to present a quality analysis side by side with a firm level productivity analysis.

We will rely on the System GMM estimator to supplement our analysis of the impact of the FTA on firm productivity, initially with internal instruments only and then with both internal and external instruments. We start with explaining the basic assumptions behind the GMM model. We then explain the model and the moment conditions for both the equation in first difference and equation in levels needed to run the System GMM.

GMM Assumptions

The Blundell-Bond System GMM is a widely used estimator designed for dynamic panel analysis. It is based on the following assumptions regarding the data generating process as enumerated in Roodman (2006):

1. The dependent variable has a dynamic form i.e., it is based on the variables own past realizations.
2. The independent variables (regressors) may be endogenous i.e., correlated with past and even possibly with the current values of the error term.
3. Some regressors, which may be predetermined, might not be strictly exogenous; they may be independent of the current realization, but still may be correlated with the past observations (e.g., lagged dependent variable).
4. There can be the presence of arbitrarily distributed individual fixed effects. This assumption argues against the use of cross-sectional regressions which assume the fixed effects away and mainly in favor of a dynamic panel set-up where variation across individuals over time is reported.
5. The error terms (other than the fixed effect component) may have some individual-specific patterns of serial correlation and heteroskedasticity within individuals but not across them.
6. The data has few time periods and many individual observations (small T, large N).
7. The available instruments for the analysis are "internal" based on the lagged values of the instrumented variables.

Model

Following Blundell & Bond (2007), we consider a Cobb-Douglas production function as:

$$q_{it} = \beta_l l_{it} + \beta_m m_{it} + \beta_k k_{it} + \gamma_t + \eta_i + v_{it} + \epsilon_{it} \qquad (2.22)$$

$$v_{it} = p v_{i,t-1} + e_{it} \qquad |p| < 1 \qquad (2.23)$$

$$\epsilon_{it}, e_{it} \sim MA(0)$$

Where q_{it} is log of output for firm *i* in time *t*. l_{it}, m_{it} and k_{it} are the number of workers, material and capital stock of firm *i* in time *t* (in logs). γ_t are the year fixed effects, for example a common technology shock. η_i are the firm specific time-invariant shocks. v_{it} is the autoregressive productivity shock and ϵ_{it} is the serially uncorrelated error. The model assumes that the inputs are potentially correlated with firm specific shocks η_i, with productivity shocks e_{it} and with the error term ϵ_{it}.

The model above can be represented in a dynamic form:

$$q_{it} = \beta_l l_{it} - p\beta_l l_{i,t-1} + \beta_m m_{it} - p\beta_m m_{i,t-1} + \beta_k k_{it} - p\beta_k k_{i.t-1} + pq_{i,t-1} + \gamma_t - p\gamma_{t-1} + \eta_i - p\eta_i + e_{it} + \epsilon_{it} - p\epsilon_{i,t-1} \quad (2.24)$$

or

$$q_{it} = \alpha_1 l_{it} + \alpha_2 l_{i,t-1} + \alpha_3 m_{it} + \alpha_4 m_{i,t-1} + \alpha_5 k_{it} + \alpha_6 k_{i.t-1} + \alpha_7 q_{i,t-1} + \gamma_t^* + \eta_i^* + \omega_{it} \quad (2.25)$$

This equation can now be used to run the GMM estimation[57]. The next section outlines the moment conditions used to run the estimation.

GMM Estimation in First Differences and Moment Conditions

The initial conditions are based on the standard assumptions that *($E[x_{i1}\epsilon_{it}] = E[x_{i1}e_{it}] = 0$ for $t=2....T$)* which gives the following moment conditions:

$$E[x_{i,t-s}\,\Delta\omega_{it}] = 0 \text{ where } x_{it} = (l_{it}, m_{it}, k_{it}, q_{it}) \quad (2.26)$$

for s≥2 when ω_{it}~MA(0) and for s≥3 when ω_{it}~MA(1) to allow for suitable lagged levels of variables to be used as instruments after the firm fixed effects have been removed from the equation through first differencing. This gives us the first differenced GMM estimator (Arellano & Bond, 1991).

It is worth noting however that the resulting first difference GMM estimator based on first difference to eliminate firm fixed effects and its reliance on lagged level instruments give unsatisfactory results (Mairesse & Hall; 1996). The first difference GMM estimators have poor finite sample properties giving biased and imprecise estimates. This is mainly because the lagged levels of the variables are poorly correlated with the subsequent first differences, making the instruments available for the first-differenced equations weak (Blundell & Bond;1998). To understand this, consider a model which follows an AR(1) process:

$$q_{it} = \delta q_{i,t-1} + \eta_i + v_{it} \qquad |\delta| < 1 \quad (2.27)$$

where p=0 (i.e., v_{it} is serially uncorrelated). The instruments as in the standard first differenced GMM in this case become less informative as the value of δ approaches unity and secondly when the variance of the firm specific shock η_i increases relative to the variance of v_{it}. If we consider the case where T=3, the first differenced GMM estimator corresponding to a simple instrumental variable estimator can be expressed in the following reduced form equation (IV regression):

$$\Delta q_{i2} = \alpha q_{i1} + r_i \qquad \text{for } i=1,2...N \quad (2.28)$$

[57] It is worth noting that when $\omega_{it} = e_{it}$ ~ *MA(0)* if there are no measurement errors *($var(\epsilon_{it}) = 0$)* and ω_{it} *~MA(1)* otherwise.

For a large autoregressive parameter δ or for a high variance of η_i, the least square estimator of this reduced form equation α will be very close to 0. In this case q_{i1} is only weakly correlated with Δq_{i2}[58].

Additional instruments as used in the "extended" GMM, also commonly known as the System GMM, usually yields more reasonable estimates and reduces the bias as under the standard first differenced GMM estimator. Additional instruments are incorporated based on using more informative moment conditions (Blundell & Bond, 2007). While the difference GMM is based on using lagged level of variables as instruments for the equation in first difference, the system GMM in addition to it also uses the lagged first differences as instruments for the equation in levels. The subsection below describes the additional instruments combined with the ones above to run the System GMM.

Adding the Equation in Levels

We assume that $E[\Delta l_{it}\eta_i^*] = E[\Delta m_{it}\eta_i^*] = E[\Delta k_{it}\eta_i^*] = 0$ and this initial condition satisfies $E[\Delta q_{i2}\eta_i^*] = 0$, we then get addition moment conditions as:

$$E[\Delta x_{i,t-s}(\eta_i^* + \omega_{it})] = 0 \qquad (2.29)$$

For s=1 when ω_{it}~MA(0) and for s=2 when ω_{it}~MA(1). Based on these moment conditions, suitable lagged first difference variables can now be used as instruments for the equation in levels. Both sets of moment conditions are used in the GMM estimator which contains equations in first difference and in levels. Combining these two sets of moment conditions helps us run the system GMM estimator. Blundell & Bond (2007) show how using the system GMM based on these additional moment conditions greatly improves the results from the first differenced GMM estimator based on Blundell & Bond (1998), where the autoregressive parameter was weakly identified. They show that the results improve in precision with no bias even for a small sample size and a high value of the autoregressive term[59].

Adding External Instruments

Both the difference GMM estimator and the system GMM estimator rely either primarily or exclusively on "internal" instruments. However, both estimators allow the use of external instruments instead, or in addition to, the internal instruments. According to Roodman (2006) given the importance of good instruments this option is worth giving a serious thought. For this, we use two additional external instruments for material and labor in addition to the internal instruments used in the analysis.

For the labor we use the instrument based on de Roux et al. (2020). We take advantage of the fact that the national minimum wage changed during our sample period. For this we construct a measure of "bite" based on the minimum wage defined as:

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[58] We direct the reader to Blundell & Bond (1998) for a detailed discussion on this. Based on a Monte Carlo study they use different values of autoregressive parameter (δ in our case) and show that the first difference GMM estimator performs poorly as this parameter increases in its value.
[59] We direct the reader towards Blundell & Bond (2007) section 3.3 and 3.4 for the discussion on the validity of the System GMM.

$$B_{it} = \frac{MW_t}{W_{it}^l} \qquad (2.30)$$

where MW_t is the national minimum wage[60] and W_{it}^l is the average wage per worker for firm *i* in time *t*[61]. This measure of bite is then interacted with the change in national wage[62]:

$$\Delta z_{it,labor} = B_{i,t-1} * \Delta ln(MW_t) \qquad (2.31)$$

The predicted change in wage i.e., $\Delta z_{it,labor}$ serves as an instrument for labor choice by firm *i* at time *t*.

For materials we propose and then implement an instrument based on the weighted output price of other goods using a particular input. We construct this instrument using the following steps.

1. First, we identify all the material inputs used in the textile sector by firm *i* at time *t*.
2. For each material input X_k, we identify all the outputs (products) produced by any firm using that input within the textile sector at time *t*.
3. We find the average price of each output Y_j that uses input X_k. We do this by aggregating the different firm-level output prices of Y_j using weights based on firm *i*'s production of product Y_j in time *t*. For example, if input X_1 produces output Y_2 which is produced by 10 different firms at time *t*, we aggregate the prices of output Y_2 (10 different prices in this case) by weights to come up with an average price for output Y_2.
4. Next, for each input X_k we calculate the average price of all outputs using it. Taking the prices of all the outputs input X_k produces, we apply the industry share of each output Y_j as weights to get the average price of products using input X_k. So, if input X_1 produces output Y_2 and output Y_3, and we have the average price of output Y_2 and output Y_3 from step 3, we average these average prices to get a single output price for input X_1. This gives us the input-level instrument for each input for time *t*.
5. Finally, we aggregate the input-level instruments to the firm level as a weighted average. We take the input-level instruments for all inputs used by firm *i* and weight them based on each input's cost share in firm *i*'s expenditures. For example, if firm *i* at time *t* uses input X_1 and X_2 we average the instruments for each input obtained in step 4 at the firm level, using the cost shares of X_1 and X_2 as weights. This gives us the instrument for materials at the firm level that is based on the weighted output prices of other goods. We then predict the change in the weighted output prices of other goods $\Delta z_{it,material}$ as an instrument for material choice by firm *i* at time *t*.

We run the system GMM both with and without the external instruments using the xtabond2 command in Stata as described by Roodman (2009). We use the two-step system GMM which in addition to the errors (which are already robust) also corrects for the Windmeijer (2005) correction i.e., the finite sample correction[63].

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[60] MW_t is annualized by multiplying the monthly wage with 12.

[61] W_{it}^l is calculated as firm level annual wage bill divided by the number of workers.

[62] Roux et.al (2020) use bite from t-2 to avoid any correlation with the lag of the measurement error. In our analysis the gap between each time period is of 5 years so we use bite from t-1.

[63] Not correcting for it biases the standard errors downwards since a finite sample lacks the adequate information to estimate a large matrix given that the variance matrix of the moments is quadratic in instrument count which then makes it quartic to the time dimension *t*. We use a lag level of *t-1* in the analysis where the next time period is with a gap of 5 years in our dataset.

Once the system GMM is run we predict the X$\hat{\beta}$ matrix where $\hat{\beta}$ represents the estimated parameter vector. Using this, we back out the residuals i.e., the productivity estimates, and then we can estimate the impact of the changes in tariffs under the FTA on changes in firm productivity.

- ***Gandhi, Navarro, and Rivers (2020) Methodology***

Gandhi et al. (2020), hence GNR, argue that, absent an independent source of variation, the output elasticities are similarly not identified using ACF-type moment conditions applied to a gross output production function, but offer an alternative technique for estimating the output elasticity of materials through a transformation of the firm's first order condition.

GNR's technique was developed specifically for the case of gross output production functions. Given the collinearity that arises when estimating the output elasticity of materials as the fully flexible input in a gross output production function, they introduce an addition restriction in the form of the firm's first order condition. This first order condition, defining the firm's demand for the flexible input materials, also contains information about the production function, and can be transformed into a "share equation" that nonparametrically identifies the output elasticity with respect to materials (GNR, 2020, Theorem 2). From this output elasticity, they form a partial differential equation for the production function and integrate it, then estimate the constant of integration using moments based on the innovation in productivity that follows a Markov process. This last step recovers the capital and labor coefficients, as materials have already been controlled for with the materials elasticity integral.

GNR Assumptions

1. There is perfect competition both in the intermediate input and output markets for the majority of the analysis. Hence, the firms are price takers in both the markets, with ρ_t denoting the common intermediate input price and P_t denoting the common output price facing all firms in period *t*. Firms maximize expected discounted profits.
2. If an input's optimal period *t* choices are affected by lagged values of that same input, then we say the input is dynamic. If an input is neither predetermined nor dynamic, then we say it is flexible. We refer to inputs that are predetermined, dynamic, or both as non-flexible.
3. Following the proxy variable literature, the Hicks neutral productivity shock v_{jt} is decomposed as $v_{jt} = \omega_{jt} + \varepsilon_{jt}$, where ω_{jt} is known to the firm before making its period *t* decisions and ε_{jt} is an ex-post i.i.d. shock realized only after period *t* decisions are made. The production function is differentiable in all inputs and is concave in *m*.

The Model

Output is given by:

$$y_{jt} = f\left(k_{jt}, l_{jt}, m_{jt}\right) + v_{jt} \quad (2.32)$$

The Hicks neutral productivity shock v_{jt} is decomposed as $v_{jt} = \omega_{jt} + \varepsilon_{jt}$, where ω_{jt} is known to the firm before making its period *t* decisions but ε_{jt} is an ex-post productivity shock realized only after period *t* decisions are made.

The firm's own productivity, ω_{jt}, evolves in the same way as in the proxy/control variable techniques like Olley-Pakes:

$$\omega_{jt} = h(\omega_{jt-1}) + \eta_{jt} \qquad (2.33)$$

where η_{jt} is the shock or innovation to the firm productivity ω_{jt} in period *t*.

A predetermined input is a function of the information set of a prior period, so that:

$$x_{jt} = \mathbb{X}\left(\mathrm{L}_{jt-1}\right) \in \mathrm{L}_{jt}$$

Capital and labor are predetermined, so that $k_{jt}, l_{jt} \in I_{jt-1}$. But materials or intermediate inputs, however, are freely flexible:

$$m_{jt} = \mathbb{M}\left(k_{jt}, l_{jt}, \omega_{jt}\right)$$

Given that capital and labor are dynamic inputs, firms choose intermediate inputs or materials, M_{jt}, to maximize profits in period *t*:

$$\underset{M_{jt}}{Max}\, P_t E[F\left(k_{jt}, l_{jt}, m_{jt}\right)e^{\omega_{jt}+\varepsilon_{jt}} \mid I_{jt}] - \rho_t M_{jt} \qquad (2.34)$$

which has first order condition:

$$P_t \frac{\partial}{\partial M_{jt}} F\left(k_{jt}, l_{jt}, m_{jt}\right)e^{\omega_{jt}}\varepsilon = \rho_t \qquad (2.35)$$

Where the expectation of the ex-post shock in the *level* of output is a free parameter:

$$\varepsilon = E[e^{\varepsilon_{jt}} \mid I_{jt-1}] = E[e^{\varepsilon_{jt}}]$$

(2.35) is transformed into the demand for intermediate inputs m_{jt}:

$$m_{jt} = \mathbb{M}\left(k_{jt}, l_{jt}, \omega_{jt} - d_t\right) = \mathbb{M}\left(k_{jt}, l_{jt}, \omega_{jt}\right) \qquad (2.36)$$

where d_t is defined as: $d_t \equiv ln\left(\frac{\rho_t}{P_t}\right) - ln\varepsilon$

The restrictions implied by profit maximization along with lagged inputs as instruments will nonparametrically identify the production function and productivity. This is because: i) the production and the intermediate input demand functions are functionally dependent, since input demand, $\mathbb{M}$, is derived from the firm's first order condition from the profit function containing the production function, *f*, and because the materials demand, $\mathbb{M}$, is monotonic in ω_{jt}.

GNR take the log of both sides of (2.35), subtract this from the production function, add ln$M$ to both sides and rearrange to get:

$$s_{jt} = ln\varepsilon + ln\,(\frac{\partial}{\partial m_{jt}} f(k_{jt}, l_{jt}, m_{jt})) - \varepsilon_{jt} \qquad (2.37)$$

$$\equiv\; ln\varepsilon + lnD^{\varepsilon}\,(k_{jt}, l_{jt}, m_{jt}) - \varepsilon_{jt}$$

where $s_{jt} \equiv ln\frac{\rho_t M_{jt}}{P_t Y_{jt}}$ is the (log) intermediate input share of output.

Since $E[\varepsilon_{jt} \mid k_{jt}, l_{jt}, m_{jt}] = 0$, the output elasticity of the flexible input and ε_{jt} can both be recovered by regressing the shares of intermediate inputs s_{jt} on the vector of inputs (k_{jt}, l_{jt}, m_{jt}).

Theorem 2: Under the assumptions listed at the beginning of the section, and that ${p_t}/{P_t}$ (or the relative price-deflator) is observed, the share regression in equation (2.37) nonparametrically identifies the flexible input elasticity $\frac{\partial}{\partial m_{jt}} f(k_{jt}, l_{jt}, m_{jt})$ of the production function almost everywhere in (k_{jt}, l_{jt}, m_{jt}).

Theorem 2 shows that, by taking full advantage of the economic content of the model, we can identify the flexible input elasticity using moments on ε_{jt} alone.

The next step in our approach is to use the information from the share regression to recover the rest of the production function nonparametrically. The idea is that the flexible input elasticity defines a partial differential equation that can be integrated up to identify the part of the production function f related to the intermediate input m:

$$\int \frac{\partial}{\partial m_{jt}} f(k_{jt}, l_{jt}, m_{jt}) dm_{jt} = f(k_{jt}, l_{jt}, m_{jt}) + \mathfrak{C}(k_{jt}, l_{jt}) \qquad (2.38)$$

GNR subtract equation (2.38) from the production function (2.32) and re-arrange to obtain:

$$\mathcal{Y}_{jt} \equiv y_{jt} - \varepsilon_{jt} - \int \frac{\partial}{\partial m_{jt}} f(k_{jt}, l_{jt}, m_{jt}) dm_{jt} = -\mathfrak{C}(k_{jt}, l_{jt}) f(k_{jt}, l_{jt}) + \omega_{jt} \qquad (2.39)$$

Since $\mathcal{Y}_{jt}$ is a function of the materials input elasticity and the ex-post shock, it is technically observable by means of the share regression.

Following the main threads of the firm-level productivity literature (dynamic panel and the proxy variable), GNR generate moments based on the Markovian structure on productivity and the panel structure of the data in order to recover the constant of integration $\mathfrak{C}(k_{jt}, l_{jt})$. Their estimation procedure consists of two steps: 1. Estimate the share regression, and then 2. Estimate the constant of integration $\mathfrak{C}$ and the Markov process h, where h is defined from the production function as:

$$y_{it} = f(k_{jt}, l_{jt}, m_{jt}) + \omega_{jt} + \varepsilon_{jt}$$
$$= f(k_{jt}, l_{jt}, m_{jt}) + h(\emptyset(k_{jt-1}, l_{jt-1}, m_{jt-1}) + d_{t-1} - f(k_{jt-1}, l_{jt-1}, m_{jt-1}) + \eta_{jt} + \varepsilon_{jt} \quad (2.40)$$

Step 1: The Share Equation:

Given the observations $\{(y_{jt}, k_{jt}, l_{jt}, m_{jt})\}_{t=1}^{T}$ for sample firms *j* = 1, . . . , *J*, GNR use a complete polynomial of degree *r* in k_{jt},l_{jt}, m_{jt} and to use the sum of squared residuals, $\sum_{jt} \varepsilon^2$, as the objective function. For example, for a complete polynomial of degree two, our estimator would solve:

$$\min_{\gamma'} \sum_{j,t} \left\{ s_{jt} - ln \begin{pmatrix} \gamma'_0 + \gamma'_k k_{jt} + \gamma'_l l_{jt} + \gamma'_m m_{jt} + \gamma'_{kk} k_{jt}^2 + \gamma'_{ll} l_{jt}^2 \\ + \gamma'_{mm} m_{jt}^2 + \gamma'_{kl} k_{jt} l_{jt} + \gamma'_{km} k_{jt} m_{jt} + \gamma'_{lm} l_{jt} m_{jt} \end{pmatrix} \right\}^2 \quad (2.41)$$

The solution is an estimator:

$$D_r^{\varepsilon}(k_{jt}, l_{jt}, m_{jt}) = \sum_{r_k + r_l + r_m \leq r} \gamma'_{r_k, r_l, r_m} k_{jt}^{r_k} l_{jt}^{r_l} m_{jt}^{r_m}, \; with \, r_k, r_l, r_m \geq 0 \quad (2.42)$$

Step 2: The Constant of Integration and the Markovian Process:

GNR calculate the integral (2.38) using the estimator for the intermediate input elasticity, which has a closed form, using similar complete polynomial series estimators.

For a degree two estimator *(r = 2)* we would have

$$D_2\ (k_{jt}, l_{jt}, m_{jt}) \equiv \begin{pmatrix} \gamma_0 + \gamma_k \, k_{jt} + \gamma_l \, l_{jt} + \frac{\gamma_m}{2} m_{jt} + \gamma_{kk} k_{jt}^2 + \gamma'_{ll} l_{jt}^2 \\ + \frac{\gamma_{mm}}{3} m_{jt}^2 + \gamma_{kl} k_{jt} l_{jt} + \frac{\gamma_{km}}{2} k_{jt} m_{jt} + \frac{\gamma_{lm}}{2} l_{jt} m_{jt} \end{pmatrix} m_{jt} \quad (2.43)$$

With and estimate of ε_{jt} and of $D_r\ (k_{jt}, l_{jt}, m_{jt})$ in had GNR form a sample analogue of $\mathcal{Y}_{jt}$ as:

$$\widehat{\mathcal{Y}_{jt}} \equiv ln \left(\frac{Y_{jt}}{e^{\varepsilon_{jt}} e^{\hat{D}_r(k_{jt}, l_{jt}, m_{jt})}} \right) \quad (2.44)$$

After some normalization and substitutions (that can be found in GNR (2020)), they have the estimating equation:

$$\hat{y}_{jt} = -\sum_{0 < r_k + r_l \leq r} \alpha_{r_k, r_l} k_{jt}^{r_k} l_{jt}^{r_l} + \sum_{0 < a \leq A} \delta_a \, (\hat{y}_{jt-1} + \sum_{0 < r_k + r_l \leq r} \alpha_{r_k, r_l} k_{jt-1}^{r_k} l_{jt-1}^{r_l})^a + \eta_{jt} \quad (2.45)$$

GNR then use moments of the form:

$$E\left[\varepsilon_{jt}\frac{\partial lnD_r(k_{jt},l_{jt},m_{jt})}{\partial\gamma}\right]=0 \qquad (2.46)$$
$$E\ \eta_{jt}k_{jt}^{r_k}l_{jt}^{r_l}=0 \qquad (2.47)$$
$$E\ \eta_{jt}\hat{y}_{jt-1}^{a}=0 \qquad (2.48)$$

to form a standard sieve moment criterion function to estimate (α,δ).

Methodology discussion

It is useful to compare the assumptions underlying the identification of the output elasticities for each of these three methods. DGKP (2016), like other proxy variable techniques (beginning with Olley-Pakes), relies on the timing of input choices relative to the firm's knowledge of its idiosyncratic productivity following a relatively flexible Markov process but dispensing with firm fixed effects. It also imposes a monotonic relationship between firm productivity and the flexible input (materials) for the invertibility required to form the control function. Dynamic panel methods, including system GMM (Blundell & Bond, 1998), also use staggered timing of input choices but, unlike proxy variable techniques, allow for firm fixed effects. As a result, system GMM imposes more structure on the dynamics of firm-level productivity, limiting it to an AR(1) process. Stationarity (of the fixed effect) is also imposed in the second equation, that in levels using lagged-differences as instruments. Ackerberg (2020) compares how the assumptions of these models impact the precision of estimates and suggests that improvement obtained by tightening the timing assumptions by one additional period in a proxy variable method (like DGKP) is nearly equivalent to that gained by adding the stationarity assumption of system GMM. GNR assumes perfect competition in input and output markets, while system GMM and DGKP do not explicitly assume competition in either.

Each of the techniques that we have used, that is DGKP, system GMM with external instruments, and GNR, have benefits and drawbacks with respect to the quantities that we wish to estimate for the analysis of the FTA's impact on Pakistani textile producers. The structure of our data most closely matches that used in DGKP, in that we have physical output data, multiproduct firms, and concerns about heterogeneous quality and market power. Our experience in the field with this sector indicates that the timing assumptions, where capital and labor take time to adjust while materials are more flexible, matches the constraints faced by real firms. However, concerns about the correct identification of output elasticities in a gross output production function, especially for materials that are then used to calculate marginal costs and markups, leads us to consider other estimates as well. The system GMM is mostly immune from issues arising from imperfectly competitive market structures and allows the inclusion of external instruments, including demand shocks that may taint estimates of markups (Doraszelski & Jaumandreu, 2021), but the data requirements (lags of t-2) given the unbalanced panel of our data means that our estimates are limited to the subsample of firms appearing in at least the two last rounds of our panel[64]. Stationarity may be an acceptable assumption for the older, more established firms that would appear in all three waves of our data. But this might not hold for younger firms (that would be

[64] We use a lag level of *t-1* in the analysis since the next time "period" in the CMI is with a gap of 5 years.

dropped using this method) and policy changes including the tariff changes that we will evaluate here may violate stationarity even for the older firms. The GNR technique has been developed specifically for gross-output production functions, and so we also present results from it here; however, it assumes perfect competition in input and output markets, which may be unrealistic for textiles given the wide distribution we observe in goods prices in our data[65]. And neither system GMM nor GNR make adjustments for missing prices, heterogeneous quality, multiproduct firms, or input allocation bias.

V. Measuring the Impacts of the Tariff Reductions on Pakistani Textile Manufacturers

We begin by estimating the impact of the FTA on the productivity of Pakistani firms and the quality of their output. We see how the changes in productivity and quality vary by a firm's export status. We then attempt to identify the sources of the productivity gains for Pakistani exporters.

Impact on the Productivity and Product Quality of Textile Manufacturers

Using the methodologies of DGKP (2016), system GMM, and GNR to estimate firm-level productivity and Khandelwal (2010) to measure quality, we analyze the impact of the Pakistan-China FTA on Pakistan's textile sector. The firm-level tariff rate is calculated using the WTO tariff database and information from the CMI on firm-level output at the product level. The firm-level tariff rate τ_{it}^{firm} for firm *i* at time *t* is:

$$\tau_{it}^{firm} = \sum a_{jft}\ \tau_{jt} \qquad (2.49)$$

where τ_{jt} is the tariff rate imposed by China on product *j* at time *t* and a_{jft} is the revenue share of product *j* in the output of firm *f* at time *t*[66].

We measure the aggregate impact of the tariffs on the productivity and quality of the textile sector and its constituent segments. We estimate the following equation:

$$Y_{ft} = \alpha_t + \alpha_s + \alpha_{st} + \gamma\tau_{it}^{firm} + \theta \boldsymbol{C}_{ft} + \varepsilon_{ft} \qquad (2.50)$$

where Y_{ft} is log productivity ω_{ft} or log quality υ_{ft} of firm *f* at time *t* respectively. α_t are year fixed effects, α_s are segment fixed effects, and α_{st} are segment-year fixed effects. ***C*** are controls for firm *f* at time *t* which include firm average pre-FTA productivity, quality, and number of products produced, firm inputs, and dummies for missing data by year. We also run a firm fixed effects model for each specification of (2.50) as well.

In Table 2.3a, we start by looking at the impact of the tariff reductions on the productivity of all textile manufacturers and separately at those manufacturers producing in the three largest segments

[65] GNR (2017) note that, when comparing productivity using gross output data to value-added methods, the productivity advantage typically enjoyed by exporters is reduced, in some cases to zero; in our data, it appears to be reversed for exporters to China as compared to exporters to other destinations and even non-exporters, as the productivity distribution for exporters to China appears to be quite below the average (Figure 2.1).

[66] Since we observe the product mix change over time, we have substantial variation in tariff rates faced by firms, and we can adjust their exposure to tariffs by changing the weights a_{ift} as we observe the product share for each year.

of the textile sector, using the methodology of DGKP (2016). As there are a number of firms extant in the CMI for only one year of the survey, we present results both with and without firm fixed effects. The results show that there was a statistically significant increase in the productivity of textile manufacturers as a whole as a result of China's tariff reductions that, in the firm fixed effects specifications, is driven by increases in the productivity of manufacturers in the spinning segment, the segment least protected by China. When we divide the sample and consider the periods before and after tariffs on ASEAN goods were eliminated, we see that the tariff-induced productivity growth in Pakistan was larger in magnitude for the 2000-05 period, when ASEAN goods were more similarly tariff-rated (Table 2.3b).

Table 2.3a: Impact of Pakistan-China FTA's Tariff Changes on Firm-level Productivity and Quality in Pakistan's Textile Sector

Panel A: Impact of Firm Productivity (DGKP methodology)

	All Segments		Spinning Segment		Finishing Segment		Clothing Segment	
	OLS (1)	FE (2)	OLS (3)	FE (4)	OLS (5)	FE (6)	OLS (7)	FE (8)
τ_{it}^{firm}	-0.0485*** (0.0082)	-0.0978*** (0.0286)	-0.0354*** (0.0075)	-0.1443*** (0.0406)	-0.0782** (0.0390)	0.0227 (0.1386)	-0.0997*** (0.0293)	-0.0478 (0.0456)
N	1177	446	677	262	171	36	211	61
Net Impact of FTA	*0.0300*	*0.0604*	*0.0213*	*0.0868*	*0.0341*	*Insignificant*	*0.0368*	*Insignificant*

Panel B: Impact on Product Quality (Khandelwal 2010 methodology)

	All Segments		Spinning Segment		Finishing Segment		Clothing Segment	
	OLS (1)	FE (2)	OLS (3)	FE (4)	OLS (5)	FE (6)	OLS (7)	FE (8)
τ_{it}^{firm}	-0.0132*** (0.0019)	-0.0298*** (0.0041)	-0.0098*** (0.0012)	-0.0385*** (0.0041)	-0.0048 (0.0113)	0.0082 (0.0442)	-0.0150* (0.0077)	-0.0224* (0.0112)
N	1177	446	677	262	171	36	211	61
Net Impact of FTA	*0.0082*	*0.0184*	*0.0059*	*0.0232*	*Insignificant*	*Insignificant*	*0.0055*	*0.0083*

Authors' calculations based on regression of productivity estimates from DGKP (2016) and quality estimates from Khandelwal (2010) on firm-level tariff rates. The table presents the OLS and FE analysis of the impact of tariffs on firm's productivity and output quality for the overall textile industry and the three largest segments (as the Technical and Interior segments each consist of too few firms). Controls include pre-FTA firm productivity, pre-FTA firm quality and pre-FTA number of products; firm inputs, dummies for missing data by year, segment, year and segment-year fixed effects. The FE control additionally for firm fixed effects. We multiply the average change in tariffs overall and segment wise with the coefficients obtained to get the aggregate impact of the FTA. Robust Standard Error in parentheses.
***, **, * significant at 1%, 5% and 10% levels of significance respectively.

We also use the estimated coefficients from the productivity estimations and the actual changes in tariffs to estimate the net impact of the free trade agreement (in row 3 of Table 2.3a). Reductions in tariffs of between 7.5 and 10.5 percentage points (depending on the segment) resulted in an aggregate increase of only 3 to 8.6 percent in the productivity of Pakistani textiles.[67] Smaller gains in the finishing and clothing segments were accompanied by more substantial increases of up to 9 percent in the productivity of spinning manufacturers. We also estimate the impact of the of the tariff reductions on the quality of products produced by Pakistani textile manufacturers (Table

[67] We multiply the coefficients by the average change in tariffs, which was 61.8% to get the net impact.

2.3a, lower panel). Here too we find that the quality of products produced has increased as a result of the FTA, with the spinning sector again leading in gains. We use the actual changes in tariffs and the estimated coefficients from the quality regressions to estimate the aggregate impact of the free trade agreement on product quality, finding an increase of 1-2 percent.

Table 2.3b: Impacts of Tariff Reductions Before and After Elimination of Tariffs on ASEAN Exports, DGKP methodology

	All Firms	
	(2000-2005) FE (1)	(2005-2010) FE (2)
τ_{it}^{firm}	-.0737* (0.0419)	-.0591*** (0.0223)
N	190	236

Authors' calculations based on regression of productivity estimates from DGKP (2016) on firm-level tariff rates. FE analysis of the impact of tariffs on firm's productivity for the overall textile industry. Controls include segment and year fixed effects, and firm-fixed effects. Robust Standard Error in parentheses.
***, **, * significant at 1%, 5% and 10% levels of significance respectively.

Estimates of the impact of China's tariff reductions using productivity estimates from the system GMM and GNR methodologies are found in Table 3c. Estimates from the smaller sub-sample used in the fixed effects regressions are fairly consistent across methodologies, with statistically significant net impacts of the FTA ranging from 4.8 to 6.4 percent (Table 2.3c, col 2, 3, 4, 6 & 8). Estimates with the full sample using OLS have a much wider range (Table 2.3c, col 1, 5 & 7), with DGKP estimating a much smaller impact of the FTA (3 percent) on productivity as compared to GNR (8.6 percent).

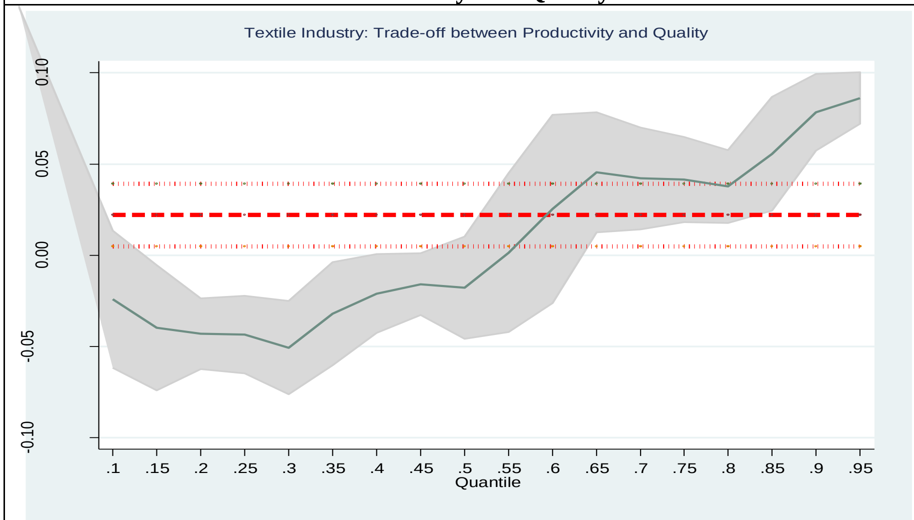
Table 2.3c: Impact of Pakistan-China FTA's Tariff Changes on Firm-level Productivity in Pakistan's Textile Sector

	DGKP (2016) Methodology		*System GMM Methodology (sample with consecutive time period data)*		*System GMM Methodology (full sample)*		*GNR (2020) Methodology*	
	OLS (1)	FE (2)	Internal IV only (3)	Internal + External IVs (4)	OLS (5)	FE (6)	OLS (7)	FE (8)
τ_{it}^{firm}	-0.0485*** (0.0082)	-0.0978*** (0.0286)	-0.1030** (0.0520)	-0.0875* (0.0498)	-0.0646** (0.0219)	-0.0717 (0.0441)	-0.1385*** (0.0242)	-0.0778* (0.0428)
N	1177	446	373	373	1177	446	1177	446
Net Impact of FTA	*0.0300*	*0.0604*	*0.0636*	*0.0540*	*0.0399*	*0.0443 (insignificant)*	*0.0855*	*0.0480*

Authors' calculations based on regression of productivity estimates from DGKP (2016), system GMM (Roodman, 2009), and GNR (2020) on firm-level tariff rates. System GMM equation in levels is estimated using one "lag" as opposed to the usual two, since 5 years pass between each round of the CMI. The table presents the OLS and FE analysis of the impact of tariffs on firm's productivity for the overall textile industry Controls include pre-FTA firm productivity, pre-FTA firm quality and pre-FTA number of products; firm inputs, dummies for missing data by year, segment, year and segment-year fixed effects. The FE control additionally for firm fixed effects. We multiply the average change in tariffs overall and segment wise with the coefficients obtained to get the aggregate impact of the FTA. Robust Standard Error in parentheses.***, **, * significant at 1%, 5% and 10% levels of significance respectively.

In Chile, Linarello (2018) found that when tariffs facing firms fell on average 5.2 percentage points, productivity increased by not only 4 percent due to the direct effect of lower foreign tariffs, but by an additional 7 percent due to reallocation, exit, and increased productivity of intermediate input suppliers. Garcia-Marin and Voigtländer (2019) find that when average tariffs fell an average of 5.6 percentage points on Chile's exports, marginal costs fell (productivity rose) on average 20 percent (where - ΔMC= +Δproductivity), to which they attribute investments around the time of export entry as the likely explanation.

Figure 2.2: Quantile Regression Plot of the correlation between Firm Productivity and Quality



Note: This figure represents the plot of coefficients from a quantile regression of log-quality on log-productivity using productivity estimates based on DGKP (2016) and N=1177. Dotted lines represent the OLS coefficient and its confidence interval. The solid line represents the coefficients from the quantile regression and the shaded area represents its confidence interval.

On average, productivity and quality appear to be complements given that they both rise in response to the FTA driven tariff reductions. To understand whether these averages are masking heterogeneity among firms, we regress log-quality on log-productivity in a quantile regression using the more modest DGKP productivity estimates. We see from Figure 2.2 that the firms with the greatest productivity growth also increased quality, but that quality fell amongst the firms with the least productivity growth. On average, productivity and quality growth are complements, but not for all firms, especially those at the lower productivity growth quantiles.

Exporters vs. Non-Exporters

We have seen that while the impact of the free trade agreement on firm-level productivity and product quality are positive and statistically significant, they are not large. One question that arises is whether the impact varies not only across segments but also whether gains were restricted to those firms who were already exporters, and if exporters to China experienced larger gains. Exporters are already known to be fundamentally different from non-exporters. In addition, prior exporting experience may also make them better placed to gain from the greater access to Chinese markets. Firms already exporting to China would also have the benefit of established relationships, knowledge of the market, and experience with customs procedures.

In order to analyze how the impact of the FTA varies for firms according to their export status, we divide the firms into three categories (i) firms active in the Chinese market *(exporters to China)* (ii) firms active in the international market but which have never been active in China *(exporters to other destinations)* and finally (iii) firms that have never been active in the international market *(non-exporters)*. We estimate the following equation:

$$Y_{ft} = \alpha_t + \alpha_s + \alpha_{st} + B\big(\left(Export\ Status, Export\ Status * \tau_{it}^{firm}\right): \beta, \delta\big) + \theta \boldsymbol{C}_{ft} + \varepsilon_{ft} \quad (2.51)$$

The equation is similar to (2.50) with the only difference being that now instead of measuring the average impact of tariffs we replace it with *B (Export Status, Export Status** τ_{it}^{firm}*)*, containing dummies for the export status and its interaction with the tariff rate from China faced by the firm *f* at time *t*. The δ represent the coefficients of the export status interacted with firm-level tariffs, our main variables of interest.

Results are presented in Table 2.4 which show that exporters to all destinations and non-exporters alike experienced increases in productivity as a result of China's reduction in tariffs. While the magnitudes differ, the increase in productivity was greater and statistical significance was higher regardless for exporters to China of the technique employed for measuring productivity (Table 2.4, col. 1-3). Non-exporters were also positively impacted by the tariff changes using DGKP and GNR to measure productivity. We observe a similar pattern with quality in column 4.

We conduct a robustness check of the main results holding the product mix fixed in generating the firm-level tariff measure. Doing this, the productivity and quality effects of tariff changes maintains its statistical significance and magnitude. For exporters to China, the coefficient estimate is almost identical to the results in Table 2.4, and the coefficients for non-exporters and exporters to other destinations goes up slightly. This is true for both the OLS and firm fixed-effects specifications.

In Figure 2.3, we repeat the same quantile regression analysis of log quality on log productivity according to the export status of the firm using the DGKP estimates. We see that the elasticity of productivity to quality is almost universally positive for exporters, especially exporters to China, and negative for most non-exporters. Given that exporters to China raised quality along with productivity, it is indeed possible that physical output productivity could have been larger in magnitude without the quality improvements.

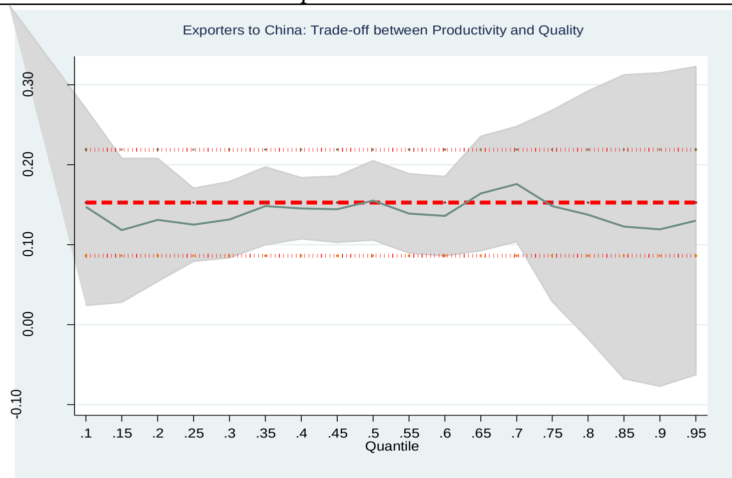
Table 2.4: Impact of Pakistan-China FTA's Tariff Changes by Export Status on Firm-level Productivity and Quality in Pakistan's Textile Sector

Panel A: OLS				
	Productivity			Quality
	DGKP (2016) *(1)*	*System GMM* *(2)*	*GNR (2020)* *(3)*	*OLS* *(4)*
Exporters to China*τ_{it}^{firm}	-0.0914*** (0.0267)	-0.1376** (0.0684)	-0.1764** (0.0655)	-0.0136** (0.0045)
Exporters to Other Destinations*τ_{it}^{firm}	-0.0300** (0.0136)	-0.0484 (0.0402)	-0.0689* (0.0378)	-0.0125** (0.0027)
Non-Exporters*τ_{it}^{firm}	-0.0505*** (0.0084)	-0.0048 (0.0232)	-0.0694** (0.0256)	-0.0132*** (0.0021)
N	1177	1177	1177	1177
Panel B: Fixed Effects				
	Productivity			Quality
	DGKP (2016) *(1)*	*System GMM* *(2)*	*GNR (2020)* *(3)*	*FE* *(4)*
Exporters to China*τ_{it}^{firm}	-0.1311* (0.0762)	-0.2508** (0.1272)	-0.2918** (0.1148)	-0.0359*** (0.0056)
Exporters to Other Destinations*τ_{it}^{firm}	-0.0907** (0.0383)	0.0404 (0.0632)	0.0723 (0.0582)	-0.0202*** (0.0052)
Non-Exporters*τ_{it}^{firm}	-0.0971** (0.0293)	-0.0907* (0.0466)	-0.1025** (0.0437)	-0.0315*** (0.0042)
N	446	446	446	446

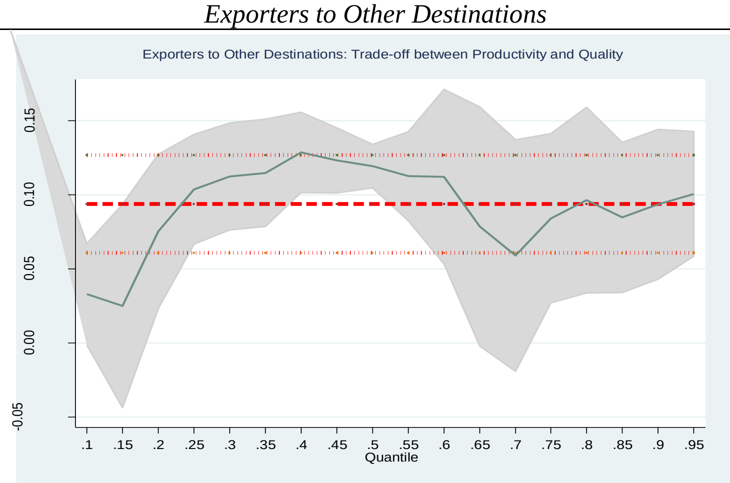
Authors' calculations based on regression of productivity estimates from DGKP (2016) and quality estimates from Khandelwal (2010) on firm-level tariff rates. The table presents the OLS and FE analysis of the impact of tariffs on firm's productivity and output quality for firms according to their export status. Controls include pre-FTA firm productivity, pre-FTA quality and pre-FTA number of products, firm inputs, dummies for missing data by year, segment, year and segment-year fixed effects. Robust standard errors in parentheses.***, **, * significant at 1%, 5% and 10% levels of significance respectively.

Figure 2.3: Quantile Regression Plot of the correlation between Firm Productivity and Quality according to Firm Export Status

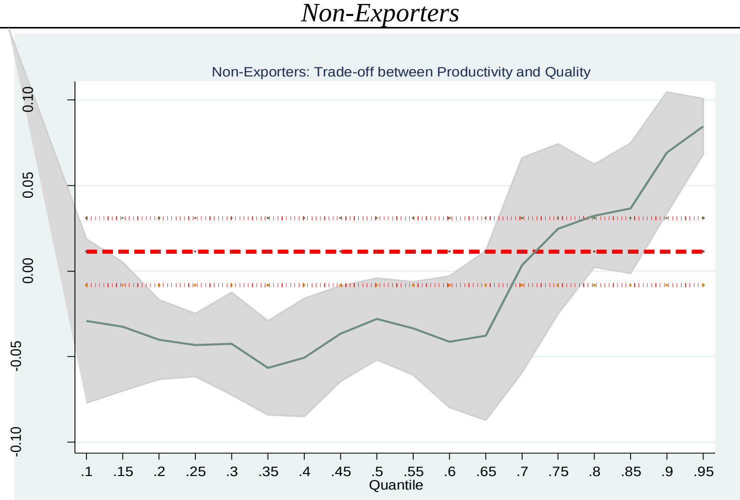
Exporters to China



Exporters to Other Destinations



Non-Exporters



Note: This figure represents the plot of coefficients from a quantile regression of log-quality on log-productivity using productivity estimates based on DGKP (2016) and N=1177. Dotted lines represent the OLS coefficient and its confidence interval. The solid line represents the coefficients from the quantile regression and the shaded area represents its confidence interval.

Could geographically induced spillovers from exporters to non-exporters help explain non-exporters' gains?

Given that the free trade agreement has had an impact on both exporting and non-exporting firms, it is important to understand why non-exporting firms would be indirectly impacted, especially given the fact that so few non-exporters became exporters after the implementation of the free trade agreement. The literature on spillovers gives us a potential answer: when exporters benefit from the lower tariffs which then leads to productivity related benefits to downstream or horizontally placed non-exporters (such as labor, materials or production process-related learning benefits) who are geographically proximate to these exporters. Linarello (2018) suggests another mechanism: that downstream exporters' tariff reductions can induce upgrading on the part on non-exporting intermediate input suppliers.

Since our data enables us to determine geographic locations of firms, we test to see if having exporters with higher productivity within 5 or 10 km induces changes in the productivity of non-exporters. We divide the exporters within these distances into upstream exporters, downstream exporters or horizontal exporters based on the goods that the exporters are producing in relation to the product produced by the non-exporters[68]. So, for example, if a non-exporter's main active segment (or only segment in case of single segment firm) is finishing, all spinning exporters within the same radius will be classified as *upstream firms* and all exporters belonging to interior, clothing or technical will be considered as *downstream firms*. An exporter who is also from the finishing sector will neither be considered an upstream or a downstream firm (at the same *horizontal level*).

For this analysis we estimate the following equation:

$$Y_{f\,post-TA}^{Non-exp} = \alpha_0 Y_{f\,post-FTA}^{UpExp} + \alpha_1 Y_{f\,post-FTA}^{DownExp} + \alpha_2 Y_{f\,post-FTA}^{HorizExp} + \gamma\tau_{i,post}^{firm} + \epsilon_{ft} \quad (2.52)$$

We define $Y_{f\,post\,FTA}$ as the post-FTA productivity and quality respectively for firm *f* where the superscript depicts the value for each type of firm, based on the segment the exporter is active in relation to the non-exporter.

In order to estimate equation (2.52) we use an instrumental variable analysis instrumenting for the post-FTA productivity of the exporter that is upstream, downstream or at the horizontal level for the non-exporter. For all of the exporters post-FTA, we identify the other exporters located within their 5 km and 10 km radius. In the first stage, we regress the post- FTA outcome on the pre-FTA values of the proximate exporters for exporter type *i_Exp*:

$$Y_{f\,post-FTA}^{i\_Exp} = \alpha_0 Y_{f\,pre-FTA}^{UpExp} + \alpha_1 Y_{f\,pre-FTA}^{DownExp} + \alpha_2 Y_{f\,pre-FTA}^{HorizExp} + \gamma\tau_{i,post}^{firm} + \epsilon_{ft} \quad (2.53)$$

where $i\_Exp = UpExp\,,\, DownExp\,,\, or\, HorizExp.$

[68] We define the segments from upstream to downstream as follows: Spinning→Finishing→ Interior, Clothing, & Technical. A horizontal sector is neither upstream nor downstream.

We then use the predicted values of each $\hat{Y}^{UpExp}_{fpost-FTA}$, $\hat{Y}^{DownExp}_{fpost-FTA}$ and $\hat{Y}^{HorizExp}_{fpost-FTA}$ in equation (2.52) to estimate the impact on the non-exporters Post FTA. The results of the first-stage regressions are in Appendix 2.2.

Table 2.5 shows the results of the spillover analysis for the productivity and quality spillovers after estimating (2.52). The results in Panel A show that the productivity of non-exporters increases if they are within 5 or 10 kilometers of more productive upstream exporters, with spillovers larger the closer is the proximity. These results contrast with Linarello (2018), where non-exporters increased productivity in response to *downstream* exporters.

The results in the Panel B shows that the quality of products produced by non-exporters increases when these firms are within 5 or 10 kilometers of upstream exporters producing higher quality products; this implies that quality gains by nearby exporters producing goods that may act as inputs for non-exporters has a positive impact on the quality of goods produced by non-exporting firms. This is somewhat similar to Bajgar and Javorcik's (2020) finding that the presence of upstream multinationals is associated with higher quality output of exporters. Panel B also shows that the quality of products of non-exporters decreases if these firms are within 5 or 10 kilometers of horizontal exporters (neither up nor downstream) producing higher quality products, possibly due to local competition over labor or materials.

Table 2.5: Productivity and Quality Spillovers of Exporters to Non-Exporters in Pakistan's Textile Sector

Panel A: Second Stage Results: Productivity of Non-Exporters Post FTA		
	Within 5 KM	*Within 10KM*
Post-FTA Productivity of Exporters classified as:		
Upstream Firms	0.3239*** (0.0527)	0.2883*** (0.0616)
Downstream Firms	-0.0029 (0.0197)	-0.0028 (0.0245)
Horizontal Level Firms	-0.0432 (0.0442)	-0.1742 (0.0893)
Panel B: Second Stage Results: Quality of Non-Exporters Post FTA		
	Within 5 KM	*Within 10KM*
Post-FTA Quality of Exporters classified as:		
Upstream Firms	0.0727*** (0.0105)	0.0429*** (0.0104)
Downstream Firms	-0.0331 (0.0207)	-0.0001 (0.0136)
Horizontal Level Firms	-0.0259** (0.0128)	-0.0350** (0.0106)

This table shows the impact of geographical spillovers of exporters on the non-exporters, depending on whether exporters are upstream, downstream or horizontally placed in relation to each non-exporter. Panel A shows the results for productivity spillovers for productivity measured using DGKP while Panel B shows the results for quality spillovers. We use an instrumental variable analysis using pre-FTA productivity (quality) of exporters in the close proximity as instruments. This table presents the second stage results for equation (6). Controls include tariff rates, missing upstream and missing downstream dummies, and the predicted values of $\hat{Y}^{UpExp}_{fpost-FTA}$, $\hat{Y}^{DownExp}_{fpost-FTA}$ and $\hat{Y}^{HorizExp}_{fpost-FTA}$ from the first stage.
N=220, Robust standard errors in parentheses. ***, **, * significant at 1%, 5% and 10% levels of significance respectively.

Our results suggest that non-exporters were passive beneficiaries of the free-trade agreement, since the effects were limited to downstream non-exporters. There does not appear to have been any significant upgrading of upstream non-exporters that would extend the impacts of the tariff reductions up the supply chain.

VI. Conclusion

Recent years have witnessed a growing number of bilateral trade agreements. While researchers have found that these trade agreements are accompanied by increases in bilateral trade flows, the impact of these trade agreements on firms (especially those in developing countries) has been understudied. We use the trade agreement between China and Pakistan as an example to see the impact of tariff reductions on firm performance in a developing economy.

Analyzing the impact on Pakistani textile manufacturers, we find that while the trade agreement lead to sustained reductions in tariffs and higher trade flows, lower Chinese tariffs did little to induce local firms to become exporters to China. The firms that did export to China experienced small increases in their productivity and quality (which were smaller than that found in the cases of other developing countries that entered in trade agreements) which were more pronounced in the early years of the trade liberalization process.

While the impacts on Pakistani exporters was smaller than what has been noted in the case of other countries that have entered trade agreements, we do find evidence of productivity and quality spillovers from exporting to non-exporting firms as a result of the trade agreement as well as increases in the quality of products produced by these non-exporting firms. Testing for this, we find that productivity spillovers occurred for non-exporters downstream from geographically proximate, higher productivity exporters.

Increased access to the Chinese market did not lead to large improvements in the productivity of exporters. Instead of pushing upstream suppliers to increase productivity and quality as has occurred other contexts, downstream firms in Pakistan instead were passive recipients the limited improvements made by exporters. Along with increased competition from ASEAN suppliers, these factors may help to explain the stunted impact of the FTA on the Pakistani textile sector.

Our results point to relatively small benefits that accrued to Pakistani textile manufacturers as they competed with ASEAN textile exporters in the Chinese market. This study provides some lessons for developing countries in light of the sustained push towards trade agreements, especially by large countries such as China. Developing countries that enter into these agreements may experience increases in trade flows as a result of lower tariffs, but they may not see significant improvements in productivity and competitiveness as a result of these agreements in the short-term.

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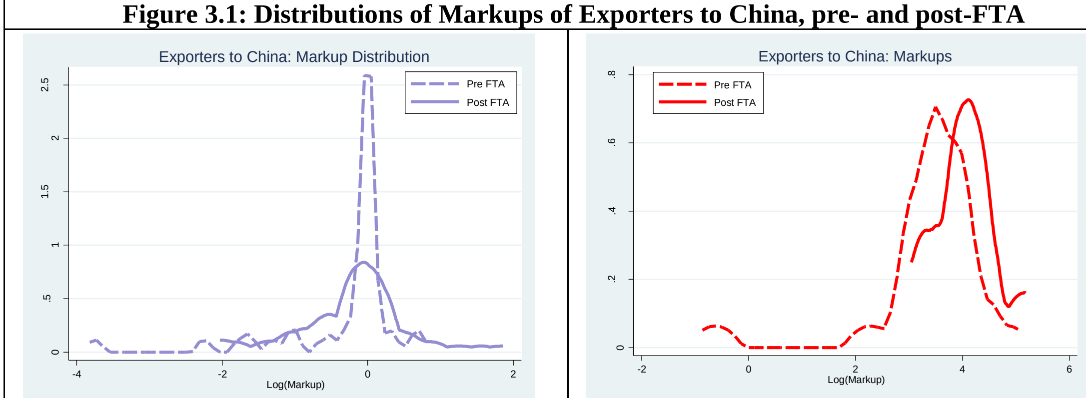
3. Paper III: Measuring changes in product mix and markups as a result of the FTA: An analysis of the Pakistani firms in response to gaining market access to China

I. Introduction

Pakistan and China entered the Free Trade Agreement in 2006 where both the countries lowered tariffs to increase trade flows. In the previous chapter we analyzed the impact of greater access to Chinese markets (as a result of China lowering its tariffs) on the productivity and quality of the textile manufacturers in Pakistan. Results showed that the benefits of the FTA were small in terms of productivity and quality improvements as compared to other developing countries and various FTAs. However, we did find evidence of spillover gains in productivity and quality to the non-exporters located in close proximity. In this chapter, we focus on the sources of productivity gains. We explore how these Pakistani textile firms adjust their input usage and product mix because of the FTA and how they respond by adjusting their markups, prices and marginal cost.

Figure 3.1-3.3 show the distribution of firm-level markup, prices, and marginal cost both before (2000-05) and after (2010) the Pakistan-China Free Trade Agreement went into effect for exporters to China. Using DGKP's (2016) methodology, firms exporting to China have wider distributions in their markups and marginal costs but a narrower and slightly lower average price distribution after the free-trade agreement[69]. The figures for product-level distributions based on DGKP (2016) can be found in Appendix 3.1. On the other hand, the system-GMM and GNR (2020) methodologies indicate that exporters to China increased markups and prices, but that there was little change in marginal cost[70].

Figure 3.1: Distributions of Markups of Exporters to China, pre- and post-FTA



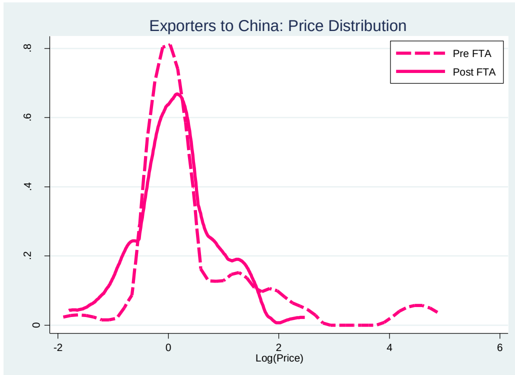
DGKP (2016) methodology	System GMM/ GNR (2020) methodologies

Source: Authors' Calculations based on CMI Punjab 2000-2001, 2005-06, 2010-11.

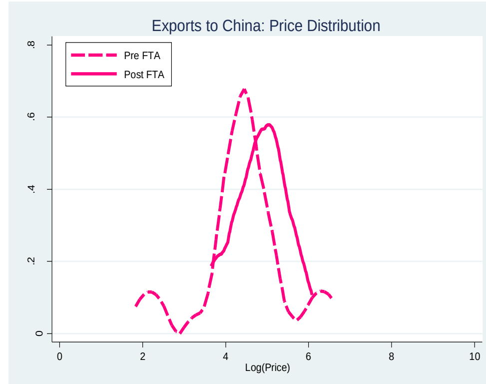
[69] We aggregate the product-level prices, marginal costs, and markups obtained with the DGKP (2016) methodology to the firm level using firm product shares. With DGKP (2016), markups and marginal costs of exporters to other destinations and non-exporters do not appear to have a discernible pattern but are rather more diffuse post-FTA.

[70] The system-GMM and GNR (2020) methodologies estimated similar output elasticities for materials, so that there was little difference in the distributions generated.

Figure 3.2: Distributions of Prices of Exporters to China, pre- and post-FTA



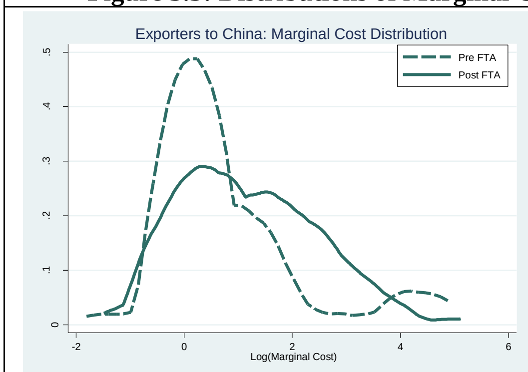
DGKP (2016) methodology



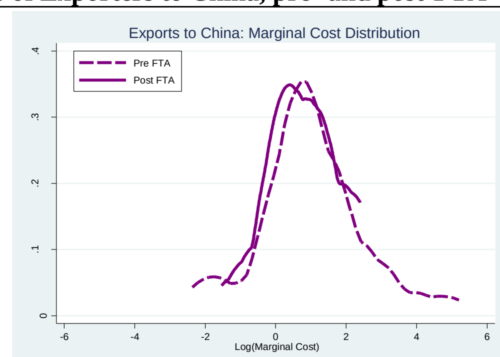
System GMM/ GNR (2020) methodologies

Source: Authors' Calculations based on CMI Punjab 2000-2001, 2005-06, 2010-11.

Figure 3.3: Distributions of Marginal Costs of Exporters to China, pre- and post-FTA



DGKP (2016) methodology



System GMM/ GNR (2020) methodologies

Source: Authors' Calculations based on CMI Punjab 2000-2001, 2005-06, 2010-11.

Studies of multi-product firms have found that firms also adjust their product mixes as a result of increased competition in foreign markets by inducing firms to reduce their number of products and focus on their core competencies which results in firm-level productivity gains (Fan et al., 2018; Mayer et al., 2014). However, given the uncertainties of exporting, firms often begin by exporting a variety already produced for the home market (Iacovone & Javorcik, 2010); this suggests that multi-product firms might be better placed to take advantage of new export opportunities.

The literature has also explored how exporters adjust prices and markups in response to trade policy changes or export market entry, although regular patterns are still emerging. When India's trade liberalization led firms to face more competition from abroad but also gave them access to cheaper imported inputs, firms reduced prices less than marginal costs fell, thereby increasing markups (DGKP, 2016). In contrast, liberalization of tariffs induced by WTO accession led Ghanaian firms to reduce markups (Damoah, 2021). Brandt et al. (2017) found a mixture of the previous two effects: in China, reduced output (input) tariffs led to lower (higher) markups. As Slovenian firms gained export market access after the fall of the Eastern Bloc, exporters raised markups (De Loecker & Warzynski, 2012). On the other hand, Garcia-Marin and Voigtländer

(2019) find that price and marginal costs of firms in Chile, Colombia, and Mexico fell almost in tandem when tariff reductions of export partners increased market access abroad, so that markups increased little, if at all.

Our study will use the exogenous policy shock of reduced tariffs and export market opportunities induced by the Pakistan-China FTA to examine its impacts on the Pakistani textile sector. Specifically, in this chapter we will examine how firms adjust to input usage and product mix in response to the tariff changes. We also explore how firms change their markups, prices and marginal cost as a result of gaining greater access in the Chinese market.

II. Empirical Methodology

In this section we describe the estimation of markups and marginal cost. We estimate markups using the methodology developed by De Loecker, Goldberg, Khandelwal, and Pavcnik – DGKP (2016) and by De Loecker & Warzynsksi (2012). We discuss both of these methodologies below.

- ***De Loecker, Goldberg, Khandelwal, and Pavcnik – DGKP (2016)***

DGKP (2016) methodology is particularly applicable in the case of multi-product firms when price and physical quantity data is available, as is the case with our data. One of the contributions of this methodology is that it estimates a product-level (rather than firm-level) production function. The markups and marginal cost as a result are also estimated at the product level. In addition to this uniqueness, the DGKP approach avoids any strong parametric assumptions regarding consumer demand, nature of competition or market structure. Moreover, their methodology contributes to literature by addressing a number of newer biases in the production literature (but hardly addressed) including the *omitted input price bias* and *unobserved allocation of the inputs* across firms producing multiple products.

With disaggregated price and physical output data, DGKP (2016) estimate a quantity-based, gross production function that controls for simultaneity and omitted output price bias by means of a control function approach with materials as the proxy variable/flexible input. To account for omitted input prices, DGKP begin with the assumption that, when high quality inputs are complements to each other the prices of all inputs faced by the firm can be written as a function of a single output product quality. Since the manufacture of higher quality output requires higher quality inputs, output prices contain information regarding input prices. With input prices increasing monotonically in input quality, they use output prices, market share, and also the firm product dummies as a proxy for the input prices. To address the allocation of inputs within firms, DGKP (2016) rely on firms producing product firms for their estimation the production function since, in that case, there is by definition no input allocation bias. But since the choice to produce many products is not random, they also implement a correction procedure that calculates the probability that a firm will self-select into multi-product manufacturing, based on a productivity threshold and the firm's information set. In DGKP's last step, the production function is estimated with GMM using moment conditions based on the innovation in the productivity shock (along the lines of ACF (2015)), where materials are fully flexible (or static) inputs and capital and labor are dynamic inputs that depend on previous values. Below we briefly describe how DGKP (2016) use their methodology to estimate markups and the marginal cost.

Production function for the firm *f* can be expressed as in equation (3.1) where it produces product *j* at the time *t*:

$$Q_{fjt} = F_{jt}\left(V_{fjt}, K_{fjt}\right)\Omega_{ft} \qquad (3.1)$$

where Q is the physical output, V is a vector of variable inputs that are freely adjustable, K is a vector of fixed inputs that face some adjustment cost, and Ω_{ft} is the firm-specific productivity. A firm produces a discrete number of products J_{ft}[71]. Let W^{v}_{fjt} be the vector of variable input prices and W^{K}_{fjt} be a vector of dynamic input prices. Assuming that the production function F_{jt} is continuous and twice differentiable with respect to at least once variable input V_{fjt}, firms minimize costs by taking output quantity and input prices W_{fjt} as given at time *t*. The Lagrangian for the cost minimization problem for firm *f* producing the product *j* at the time *t* can be written as:

$$\mathrm{L}(V_{fjt}, K_{fjt}, \lambda_{fjt}) = \sum_{v=1}^{V} W^{v}_{fjt} V^{v}_{fjt} + \sum_{k=1}^{K} W^{K}_{fjt} V^{K}_{fjt} + \lambda_{fjt}[Q_{fjt} - Q_{fjt}((V_{fjt}, K_{fjt}, \Omega_{ft})] \qquad (3.2)$$

Taking the derivative with respect to any variable input V^{V} used in the production of product *j* and letting λ_{fjt} be the marginal cost we get

$$\frac{\partial \mathrm{L}_{fjt}}{\partial V^{V}_{fjt}} = W^{v}_{fjt} - \lambda_{fjt}\frac{\partial Q_{fjt}(.)}{\partial V^{V}_{fjt}} \qquad (3.3)$$

Rearranging and multiplying both sides of the equation with $\frac{V_{fjt}}{Q_{fjt}}$ we get

$$\frac{\partial Q_{fjt}(.)}{\partial V^{V}_{fjt}}\frac{V_{fjt}}{Q_{fjt}} = \frac{1}{\lambda_{fjt}}\frac{W^{v}_{fjt} V_{fjt}}{Q_{fjt}} \qquad (3.4)$$

The left-hand side expression of equation (3.4) represents the output elasticity with respect to the variable input V^{V} . Denoting the output elasticity as $\theta = \frac{\partial Q_{fjt}(.)}{\partial V^{V}_{fjt}}\frac{V_{fjt}}{Q_{fjt}}$ and defining the markup as $\mu_{fjt} = \frac{P_{fjt}}{\lambda_{fjt}}$, expression (3.4) can be written as:

$$\mu_{fjt} = \theta^{V}_{fjt}\left(\frac{P_{fjt}\,Q_{fjt}}{W^{V}_{fjt} V^{V}_{fjt}}\right) = \theta^{V}_{fjt}\,(\alpha^{v}_{fjt})^{-1} \qquad (3.5)$$

where α^{v}_{fjt} is the share of expenditure on input V^{V} which is allocated in the production of product *j* in the total sales of product *j*. Both the components of expression (3.5) are unobservable in the case of a multi-product firm since all the variables are indexed by product *j* in contrast to a typical firm-level analysis. In the case of a firm-level analysis, the output elasticity with respect to the variable input is directly estimated using a production function based on deflated revenues while the firm-specific input expenditure shares are directly observed in the data. In contrast, this

[71] Note that the production function *F(.)* is indexed by product *j*. This assumption implies that a single-product and a multi-product firm that produce the same product have the same production technology, although their productivity Ω_{ft} can differ.

approach relies on estimating the output elasticity separately for each product manufactured and is based on estimating the product-level expenditure share of every input[72].

Hence, DGKP (2016) develop a unique approach to estimate both output elasticity and input shares for the case of multi-product firms. Once the product-level markup is obtained, the product-level marginal cost is simply:

$$mc_{fjt} = \frac{P_{fjt}}{\mu_{fjt}} \qquad (3.6)$$

With disaggregated price and physical output data in hand, DGKP (2016) estimate a quantity-based production function that does not suffer from omitted output price bias. When prices and output are observed at the product level, a product level analysis can be conducted. This methodology does not aggregate output and prices at the firm level and hence does not assume any explicit market demand function.

We direct the reader to paper II (section IV) for a detailed discussion on how the DGKP (2016) methodology solves for *omitted input price bias* (due to quality-differentiated inputs used by firms) and the *unobserved allocation of inputs* within multi-product firms, since the typical firm-level dataset only records input expenditure data at the firm-level (rather than at the product-level). We also discuss the moment conditions and the control functions used for identification.

- ***De Loecker & Warzynsksi (2012)***

De Loecker & Warzynski (2012) introduce an empirical method for the estimation of firm level markups based on the standard cost minimization problem by relying on the variable input which have free adjustment costs. This framework estimates markups based on the output elasticity of the variable input and the share of the variable input's expenditure in total sales.

Assume firm *i* in time *t* has a production technology as follows

$$Q_{it} = Q_{it}(X_{it}^{1}, \ldots, X_{it}^{V}, K_{it}, \omega_{it}) \quad (3.7)$$

where V is a set of variable inputs like labor, materials, and other intermediate inputs. Moreover, the firm relies on the capital stock K_{it} which is dynamic in the production process. The only two assumptions to estimate marks are that $Q_{it}(.)$ is continuous and is twice differentiable with respect to its elements[73].

Assuming producers indulge in cost minimization, the Lagrangian function associated with the problem can be written as

$$\mathcal{L}(X_{it}^{1}, \ldots, X_{it}^{V}, K_{it}, \lambda_{it}) = \sum_{v=1}^{V} P_{it}^{X^{v}} X_{it}^{v} + r_{it}K_{it} + \lambda_{it}(Q_{it} - Q_{it}(.)) \quad (3.8)$$

[72] Since input allocation across products is rarely observed, most studies make assumptions on how they are allocated. Foster et. al (2008) allocate input expenditure across products based on their revenue shares while De Loecker (2011) allocates the input share based on the number of products produced by the firm.
[73] This expression can encompass both a value-added function and a gross output function. In the former case, only labor and capital enter the input set while in the former the input set in addition to labor and capital is a function other intermediate inputs e.g., materials.

where $P_{it}^{X^v}$ are the prices for the variable input v and r_{it} is the price of capital. The FOC with respect to the variable input (without adjustment cost) gives us

$$\frac{\partial \mathcal{L}_{it}}{\partial X_{it}^{v}} = P_{it}^{X^v} - \lambda_{it} \frac{\partial Q_{it}(.)}{\partial X_{it}^{v}} = 0 \qquad (3.9)$$

where λ_{it} is the marginal cost of production[74]. Rearranging and multiplying both sides of the expression by $\frac{X_{it}}{Q_{it}}$ we get:

$$\frac{\partial Q_{it}(.)}{\partial X_{it}^{v}} \frac{X_{it}^{v}}{Q_{it}} = \frac{1}{\lambda_{it}} \frac{P_{it}^{X^v} X_{it}^{v}}{Q_{it}} \qquad (3.10)$$

The above expression implies that the output elasticity of the variable input X_{it}^{v} should equal to its cost share $\frac{1}{\lambda_{it}} \frac{P_{it}^{X^v} X_{it}^{v}}{Q_{it}}$. This can be referred to as the *conditional cost function* as under this cost minimization problem we can simply condition on the use of dynamic inputs like capital (or any other inputs which has adjustment costs) without having to solve for the full firm dynamic problem. This helps in avoiding having to make more assumptions needed to estimate markups. It's worth noting that this holds for any cost minimizing firm irrespective of the competition and underlying demand structure.

As the last step to recover markups μ_{it} let it be defined as $\mu_{it} \equiv \frac{P_{it}}{\lambda_{it}}$. Using this definition of markup[75] the above equation can be written as

$$\theta_{it}^{X} = \mu_{it} \frac{P_{it}^{X} X_{it}}{P_{it} Q_{it}} \qquad (3.11)$$

where θ_{it}^{X} is the output elasticity of input X_{it}. Rearranging we get

$$\mu_{it} = \theta_{it}^{X} (\alpha_{it}^{X})^{-1} \qquad (3.12)$$

where α_{it}^{X} is the share of the expenditure of input X_{it} in the total sales $P_{it}Q_{it}$. To estimate the markups, one only requires estimating the output elasticity of one (or more) of the variable input(s) which can be done by estimating the production function. The latter term of the expression is directly observed in most of the micro data sets. For our analysis, we estimate the output elasticity by using an extended or system GMM estimator (Blundell & Bond, 1998) and Gandhi, Navarro, and Rivers (2020) methodology.

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[74] This is the marginal cost since $\frac{\partial \mathcal{L}_{it}}{\partial Q_{it}} = \lambda_{it}$

[75] This expression for markup as a ratio of price over marginal cost is robust in various price (static) setting models and does not depend on a particular form of price competition amongst firms. However, it will depend on the specific nature of competition amongst firms. One restriction imposed is that prices are set period by period ruling out any cost adjustments of changing prices. Markups, however, will depend on the interaction amongst firms and the strategic interaction between them. We direct the reader towards the online appendix of De Leocker & Warzynski (2012) for discussion on some leading cases in this.

The system GMM estimator uses a differenced equation (with levels of inputs as instruments) along with an equation in levels (with differenced inputs as instruments). To this, we add external instruments for labor based on changes in the minimum wage and for materials based on the weighted output price of other goods using the same input, to address concerns regarding the relationship between product quality and input demand[76]. Following de Roux et al. (2021), we measure of the "bite" of minimum wage legislation based on the ratio of the minimum wage to the average wage paid by a firm. This measure of bite is then interacted with the change in the minimum wage and the predicted change in wage serves as an instrument for the firm's labor choices. A change in the minimum wage not only shifts up the wages of the lowest paid, but puts pressure on the entire wage distribution, since skilled workers in the textile sector tend to be paid higher than minimum wages. Our instrument for materials is intended as an exogenous source of variation in input demand through prices. Since a firm's demand for input v_{fjt} will be determined not only by quality but by input price w_{fjt}, we argue that a change in the price of *other* goods that use the same input v will shift the demand for input v and can serve as an exogenous source of variation in input price w_{fjt}. Even if input quality differs, changes in the demand for a particular input quality will lead suppliers to adjust prices of the same input of other qualities as well. To begin, we create a weighted average of output prices that use a particular input in their production to proxy for the demand for each material input[77]. The instrument for each firm's material inputs is then constructed as an aggregate of these proxies for the material input demand, using the firm's input expenditure shares to create a weighted average.

GNR (2020) has been developed specifically for the case of gross output production functions. Given the collinearity that arises when estimating the output elasticity of materials as the fully flexible input in a gross output production function, they introduce an addition restriction in the form of the firm's first order condition. This first order condition, defining the firm's demand for the flexible input materials, also contains information about the production function, and can be transformed into a "share equation" that nonparametrically identifies the output elasticity with respect to materials (GNR, 2020, Theorem 2). From this output elasticity, they form a partial differential equation for the production function and integrate it, then estimate the constant of integration using moments based on the innovation in productivity that follows a Markov process. This last step recovers the capital and labor coefficients, as materials have already been controlled for with the materials elasticity integral.

We direct the reader to paper II (section IV) for a detailed discussion on the estimation of the system GMM and GNR (2020) approach.

III. Data Sources

This chapter is an extension of chapter II. We use the same data sources as in chapter II. We direct the reader to the data section (section III of paper II) for more discussion on the various data sources used in the analysis.

[76] An anonymous referee pointed out that a high-quality firm faces different demand conditions and therefore chooses its inputs in a systematically different way than a low quality firm, leading to a direct relationship between quality and inputs and necessitating an instrument that affects a firm's demand for inputs (relevance) while simultaneously affecting neither product quality nor productivity (exclusion).

[77] The average output price of an individual product j is weighted by each firm's share of good j's output. The average price of goods using input v_t is weighted by each good j's share in the industry's output.

IV. Exploring the Sources of Productivity and Quality Changes for Exporters and Non-Exporters

Our results from the previous chapter suggest that the productivity gains experienced by Pakistani textile producers as a result of tariff concessions were smaller than the productivity gains of Chilean exporters when they gained greater access to markets, even though the latter experienced smaller tariff rate reductions. Chilean firms increased productivity 11 to 15 percent according to estimates of Linarello (2018) and Garcia-Marin and Voigtländer (2019) in response to tariff reduction of less than 6 percentage points, while Pakistani firms' productivity rose by just 3 to 8.6 percent as a result of tariff reductions in the range of 7.5 to 10.5 percentage points. These studies point towards increased productivity along with intermediate input supplier's technology upgrading respectively as sources of these gains.

In this chapter we attempt to identify the sources of the productivity gains of Pakistani exporters, and, in doing so, an explanation for why the gains were relatively small. First, since investment has been found to accompany export entry and export access expansions (Bustos, 2011; Garcia-Marin & Voigtländer, 2019; Lileeva & Trefler, 2010), we measure the impact of tariff changes on capital, labor, and material usage by Pakistani textile firms. Second, following the findings that exporters concentrate on fewer products (Baldwin et al, 2012) and that this may be a source of productivity growth through larger scale, we see if the tariff reductions reduced the export diversity of firms. Third, we explore the extent to which firms adjusted mark-ups and took advantage of the tariff reductions to move along the demand curve and capture a larger market.

How did firms adjust their inputs in response to the tariff reductions?

We begin by analyzing the impact of tariff changes on the investments made by firms. We do this by testing the impact of lower tariffs on capital, labor, and material usage by Pakistani textile firms. We estimate equations similar to that in paper II. We estimate the following equation:

$$Y_{ft} = \alpha_t + \alpha_s + \alpha_{st} + \gamma\tau_{it}^{firm} + \theta\boldsymbol{C}_{ft} + \varepsilon_{ft} \qquad (3.13)$$

where Y_{ft} are the respective inputs (capital, labor, and materials) of firm *f* at time *t*. α_t are year fixed effects, α_s are segment fixed effects, and α_{st} are segment-year fixed effects. $\boldsymbol{C}$ are controls for firm *f* at time *t* which include firm average pre-FTA productivity, quality, and number of products produced, pre-FTA firm inputs, and dummies for missing data by year. We also run a firm fixed effects model for each specification of (3.13) as well.

Next, in order to analyze how the impact of the FTA varies for firms according to their export status, we divide the firms into three categories (i) firms active in the Chinese market *(exporters to China)* (ii) firms active in the international market but which have never been active in China *(exporters to other destinations)* and finally (iii) firms that have never been active in the international market *(non-exporters).*

We estimate the following equation

$$Y_{ft} = \alpha_t + \alpha_s + \alpha_{st} + B\big(\big(Export\ Status, Export\ Status * \tau_{it}^{firm}\big): \beta, \delta\big) + \theta \boldsymbol{C}_{ft} + \varepsilon_{ft} \qquad (3.14)$$

The equation is similar to (3.13) with the only difference being that now instead of measuring the average impact of tariffs we replace it with *B (Export Status, Export Status** τ_{it}^{firm}*)*, containing dummies for the export status and its interaction with the tariff rate from China faced by the firm *f* at time *t*. The δ represent the coefficients of the export status interacted with firm-level tariffs, our main variables of interest.

The results are shown in Table 3.1. We do not find that exporters to China increased investment in capital. Exporters to China may have increased their labor and materials usage, but those coefficients are only significant in the specifications without firm fixed effects. The only input that has seen strong growth as tariffs fell when firm fixed effects are included are materials, and these are effects were larger and only statistically significant for non-exporters and exporters to non-China destinations. Thus, one reason why productivity gains of the free trade agreement were small may have been a lack of investment and upgrading, in comparison to other studies of firms gaining foreign market access.

Table 3.1: Impact of Pakistan-China FTA's Tariff Changes on Firm-level Inputs in the Textile Sector

Panel A: Impact of Tariff changes on Inputs

	Capital		*Labor*		*Materials*	
	OLS (1)	FE (2)	OLS (3)	FE (4)	OLS (5)	FE (6)
τ_{it}^{firm}	-0.0786** (0.0304)	-0.0422 (0.0645)	-0.0381* (0.0206)	-0.0757* (0.0444)	-0.0721** (0.0334)	-0.1488** (0.0592)
N	1177	446	1177	446	1177	446

Panel B: Impact of Tariff changes on inputs by export status

	Capital		*Labor*		*Materials*	
	OLS (1)	FE (2)	OLS (3)	FE (4)	OLS (5)	FE (6)
Exporter to China*τ_{it}^{firm}	-0.1266 (0.0960)	-0.0647 (01253)	-0.1095* (0.0633)	-0.0610 (0.0616)	-0.2509** (0.1128)	-0.0579 (0.1029)
Exporter to Other Destinations*τ_{it}^{firm}	-0.1429** (0.0547)	0.0901 (0.1012)	-0.1241** (0.0400)	-0.0915 (0.0619)	-0.1854** (0.0620)	-0.1717* (0.0830)
Non-Exporter*τ_{it}^{firm}	-0.0638** (0.0306)	-0.0726 (0.0686)	-0.0157 (0.0195)	-0.0734 (0.0455)	-0.0382 (0.0312)	-0.1526* (0.0602)
N	1177	446	1177	446	1177	446

Authors' calculations based on OLS and FE regression analysis of the impact of tariffs on firm's input usage. Panel A shows the impact of tariffs on input directly while panel B disaggregates the effect according to the export status of the firm. Controls include pre-FTA firm productivity (DGKP methodology), pre-FTA quality and pre-FTA number of products, and firm inputs, dummies for missing data by year, segment, year and segment-year fixed effects. The FE control additionally for firm fixed effects. Robust standard errors in parentheses. ***, **, * significant at 1%, 5% and 10% levels of significance respectively.

Did firms adjust their product diversity in response to the tariff reductions?

Next, we test to see if firms diversified their products, both in terms of the number of products produced as well as the number of product segments that they produce in, as a result of the reductions in tariffs. While some of the literature has found that exporters may benefit from concentrating in fewer products, it is possible that multi-product firms may benefit from trade agreements because of have greater export opportunities for a wider range of products. In order to test this, we extend equations (3.13) and (3.14) to examine the impact of the FTA on number of products produced and the number of segments firm *f* is active in at time *t*.

Table 3.2 shows how tariff changes arising from the free trade agreement impacted the number of products and segments produced overall (Panel A) and by exporting status of the firm (Panel B). In columns 1 and 2 of Panel B, we see that exporters to China reduced their number of products the most, by about half of a product on average, and that non-exporters also became more concentrated in terms of both products and segments (column 3 of Panel B).

Table 3.2: Impact of Pakistan-China FTA's Tariff Changes on Number of Products and Segments in Pakistan's Textile Sector

Panel A: Impact of Tariff changes on number of products and segments				
	Number of Products		*Number of Segments*	
	OLS (1)	FE (2)	OLS (3)	FE (4)
τ_{it}^{firm}	0.0601** (0.0196)	0.1884** (0.0739)	0.0087** (0.0028)	0.0041 (0.0048)
N	1177	446	1177	446
Panel B: Impact of Tariff changes on number of products and segments by export status				
	Number of Products		*Number of Segments*	
	OLS (1)	FE (2)	OLS (1)	FE (2)
Exporter to China*τ_{it}^{firm}	0.1741** (0.0736)	0.5602** (0.2662)	-0.0043 (0.0113)	-0.0139 (0.0171)
Exporter to Other Destinations*τ_{it}^{firm}	0.1039** (0.0406)	0.0729 (0.1284)	0.0004 (0.0056)	0.0095 (0.0060)
Non-Exporter*τ_{it}^{firm}	0.0382** (0.0189)	0.1716** (0.0776)	0.0090** (0.0030)	0.0048 (0.0055)
N	1177	446	1177	446

Authors' calculations based on OLS and FE regression analysis of the impact of tariffs on the number of products produced by the firm and the number of segments its active in. Panel A shows the results of the impact of tariffs on number of products and segments directly while panel B disaggregates the effect according to the export status of the firm. Controls include pre-FTA firm productivity measured using DGKP, pre-FTA quality and pre-FTA number of products, firm inputs, dummies for missing data by year, segment, year and segment-year fixed effects. The FE control additionally for firm fixed effects. Robust standard errors in parentheses.
***, **, * significant at 1%, 5% and 10% levels of significance respectively.

Did firms maximize demand in response to the tariff reductions?

In this subsection we explore the impact of the free trade agreement on the prices, marginal costs, and markups of exporters and non-exporters at the firm level. The purpose of this is to see the extent to which firms adjusted mark-ups and took advantage of the tariff reductions to move along the demand curve and capture a larger market. Garcia-Marin and Voigtländer (2019) found for Chilean firms that mark-ups barely changed while prices and marginal costs fell in response to tariff reductions by export partners so that savings were passed on consumers in export markets.

In order to test this, we analyze how marginal costs and mark-ups have evolved with the FTA. We aggregate the product-level estimates from DGKP (2016) to the firm level using firm-specific product revenue shares, in addition to firm-level estimates directly obtained using system GMM and GNR to estimate output elasticities used in the De Loecker & Warzynsksi (2012) framework to estimate markups and marginal cost. We then study the impact of the FTA on marginal costs, price, and markups using equation (3.13) and (3.14). In these regressions, Y_{ft} is now markup, price, or marginal cost for firm *f* at time *t*.

Table 3.3: Impact of Pakistan-China FTA's Tariff Changes on Markups in Pakistan's Textile Sector (OLS)

Panel A: Impact of Tariff changes on Markups			
	DGKP (2016) Methodology	*System GMM Methodology*	*GNR (2020) Methodology*
	(1)	(2)	(3)
τ_{jt}	-0.0048 (0.0044)	0.0906*** (0.0197)	0.0984*** (0.0207)
N	1177	1177	1177
Panel B: Impact of Tariff changes on Markups by Export Status			
	DGKP (2016) Methodology	*System GMM Methodology*	*GNR (2020) Methodology*
	(4)	(5)	(6)
Exporters to China*τ_{jt}	0.0130 (0.0139)	0.0745 (0.0577)	0.0749 (0.0577)
Exporters to Other Destinations*τ_{jt}	-0.0096 (0.0104)	0.1101*** (0.0289)	0.1063*** (0.0287)
Non-Exporters*τ_{jt}	-0.0048 (0.0045)	0.0076 (0.0123)	0.0097 (0.0122)
N	1177	1177	1177

Authors' calculations based on OLS regression analysis of the impact of tariffs on firm-level markups. Panel A shows the results of the net impact of tariffs on markups directly while panel B disaggregates the effect according to the export status of the firm. We aggregate the product-level markups obtained with the DGKP (2016) methodology to the firm level using firm product shares. Controls include pre-FTA firm productivity, pre-FTA quality, pre-FTA number of products, and firm inputs, dummies for missing data by year, segment, year and segment-year fixed effects. Robust standard errors in parentheses.
***, **, * significant at 1%, 5% and 10% levels of significance respectively.

Table 3.4: Impact of Pakistan-China FTA's Tariff Changes on Prices in Pakistan's Textile Sector (OLS)

Panel A: Impact of Tariff changes on Prices			
	DGKP (2016) Methodology	*System GMM Methodology*	*GNR (2020) Methodology*
	(1)	(2)	(3)
τ_{jt}	0.0248** (0.0088)	0.1583*** (0.0272)	0.1596*** (0.0267)
N	1177	1177	1177
Panel B: Impact of Tariff changes on Prices by Export Status			
	DGKP (2016) Methodology	*System GMM Methodology*	*GNR (2020) Methodology*
	(4)	(5)	(6)
Exporters to China*τ_{jt}	0.0571** (0.0226)	0.1585** (0.0645)	0.1671** (0.0632)
Exporters to Other Destinations*τ_{jt}	0.0404* (0.0216)	0.0988** (0.0359)	0.1023** (0.0351)
Non-Exporters*τ_{jt}	0.0140 (0.0097)	0.1056** (0.0274)	0.1098*** (0.0273)
N	1177	1177	1177

Authors' calculations based on OLS regression analysis of the impact of tariffs on firm-level prices. Panel A shows the results of the net impact of tariffs on prices directly while panel B disaggregates the effect according to the export status of the firm. We aggregate the product-level prices obtained with the DGKP (2016) methodology to the firm level using firm product shares. Controls include pre-FTA firm productivity, pre-FTA quality, pre-FTA number of products, and firm inputs, dummies for missing data by year, segment, year and segment-year fixed effects. Robust standard errors in parentheses.
***, **, * significant at 1%, 5% and 10% levels of significance respectively.

Table 3.5: Impact of Pakistan-China FTA's Tariff Changes on Marginal Costs in Pakistan's Textile Sector (OLS)

Panel A: Impact of Tariff changes on Marginal Costs			
	DGKP (2016) Methodology	*System GMM Methodology*	*GNR (2020) Methodology*
	(1)	(2)	(3)
τ_{jt}	0.0297*** (0.0091)	0.0676** (0.0276)	0.0612** (0.0276)
N	1177	1177	1177
Panel B: Impact of Tariff changes on Marginal Costs by Export Status			
	DGKP (2016) Methodology	*System GMM Methodology*	*GNR (2020) Methodology*
	(4)	(5)	(6)
Exporters to China*τ_{jt}	0.0440* (0.0235)	0.0840 (0.0886)	0.0921 (0.0870)
Exporters to Other Destinations*τ_{jt}	0.0500* (0.0200)	-0.0112 (0.0426)	-0.0039 (0.0421)
Non-Exporters*τ_{jt}	0.0189* (0.0099)	0.0980** (0.0310)	0.1001*** (0.0308)
N	1177	1177	1177

Authors' calculations based on OLS regression analysis of the impact of tariffs on firm-level marginal cost. Panel A shows the results of the net impact of tariffs on marginal cost directly while panel B disaggregates the effect according to the export status of the firm. We aggregate the product-level marginal costs obtained with the DGKP (2016) methodology to the firm level using firm product shares. Controls include pre-FTA firm productivity, pre-FTA quality, pre-FTA number of products, and firm inputs, dummies for missing data by year, segment, year and segment-year fixed effects. Robust standard errors in parentheses.
***, **, * significant at 1%, 5% and 10% levels of significance respectively.

In Tables 3.3-3.5, we see the impact of the tariff changes on the firm-level markups, prices, and marginal costs. In Panel A we test the impact of tariff reductions overall for each methodology and in Panel B by the export status of the firm. Using the DGKP methodology, there was no change in firm-level average markups (Table 3.3, col 1), but there was a marked decrease, driven by exporters to other destinations, when markups are measured using either system GMM or GNR (2020)[78]. We find that prices fell for all types of firms in Table 3.4, with the greatest price cuts enacted by exporters to China. We find modest firm-level marginal cost reductions when measured by DGKP, but more substantial cuts, driven by non-exporters, when MC is measured using either of the other two methodologies (Table 3.5).

Given the more robust measurement of the (flexible) materials output elasticity using system GMM and GNR, we feel more confident about those results. They suggest that neither marginal costs nor markups declined markedly for exporters to China. Garcia-Marin and Voigtländer similarly found little change in markups for firms in Mexico, Colombia, and Chile that gained market access.

[78] Using the original product-level results obtained using the methodology of DGKP (2016), we find that marginal costs and markups of firms exporting to China fell around 5 percent and prices fell around 10 percent (Appendix 3.2). Exporters to China translated productivity gains into lower prices and markups, but these may have not been substantial enough to compete with imports from the ASEAN countries at lower tariff rates.

V. Conclusion

Over years, with growing importance of international trade there has been an increase in the number of countries entering into Free Trade Agreements to enhance bilateral trade. While a substantial amount of literature focuses on the impact of better availability of intermediate inputs (as a result of tariff reductions) on firm level outcomes, the impact of FTA on firms as a result of gaining more market access is limited. It is even more limited when studied in context to a developing country. This research contributes to the latter branch of literature where we examine the impact of tariff reductions by China on the productivity of Pakistani textile firms under the Free Trade Agreement. Our estimations in the previous chapter show that there were modest productivity gains for firms in the textile sector. In this chapter, we examine the sources of productivity gains.

Our study shows that the firms that did export to China increased their scale (with greater usage of labor and inputs) and reduced their product offerings; but these firms only experienced small increases in their productivity (which were smaller than that found in the cases of other developing countries that entered in trade agreements) which were more pronounced in the early years of the trade liberalization process. Unlike other studies that found exporting concurrent with upgrading, there was not substantial investment among those firms exporting to China in our sample. Wadho and Chaudhry (2018) found for Pakistani textile producers, for a later period than our study, innovation activities were still primarily concentrated within exporters to Europe and the U.S. While exporters to China reduced product prices as they competed with ASEAN firms exporting to China, they became relatively disadvantaged when China eliminated most tariffs on textiles coming from the ASEAN countries.

Putting our overall results together, we find that exporters to China increased both productivity and quality but failed to invest in new capital. As a result, exporters were unable to substantially decrease marginal costs or markups. Pakistani exporters concentrated on fewer products, narrowed their product scope and increased their scale as they competed in Chinese markets, but increased access to this market did not lead to large improvements in the productivity of these exporters. Along with increased competition from ASEAN suppliers, these factors may help to explain the stunted impact of the FTA on the Pakistani textile sector.

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Conclusion

This dissertation explores various dimensions of firm level productivity for the textile sector in Punjab, Pakistan. We study various aspects of productivity in light of a policy change i.e., opening up to trade. We specifically focus on the free trade agreement between Pakistan and China in 2006. Hence, this dissertation is a contribution to the trade-productivity literature. We summarize our main findings below.

Measuring Actual TFP Growth: Stripping away Omitted Price Bias and Demand Shocks

In this part of the dissertation, we study the implications of not addressing the measurement issues within the estimation of productivity. If the estimates of productivity themselves are biased, then the impact of any policy change (including trade) on productivity is questionable. Due to the unavailability of disaggregated price-output data, most of the literature relies on revenue data and uses sectoral deflators. Using sectoral deflators is problematic since the firm input prices can be correlated with firm output prices which leads to the problem of omitted price bias. The bias in this case will be the difference between to sectoral price and the firm price which is correlated with input usage. Not addressing this issue leads to the estimates of *measured* productivity as opposed to *actual* productivity.

Our data set gives us an advantage to compute *actual* productivity estimates since we have disaggregated data, not only at the firm level but at the product level. Hence, we have time, firm and product variation. Taking advantage of this unique data set we compute both *actual* and *measured* productivity estimates and see how the impact of openness to trade varies depending upon how we have estimated productivity. Next, we also test De Loecker's (2011) methodology which controls for omitted price bias by introducing demand into the system but still relies on deflated output. In addition to testing his methodology we built on it in two ways. Firstly, while De Loecker (2011) controls for demand shocks by relying on product and product-group dummies, we are better able to account for demand shocks. Instead of relying on dummies, we compute product specific demand shock for each firm *f* at time *t*. We then aggregate them at the firm level by using revenue shares. Secondly, while De Loecker (2011) uses demand shocks as a way to control for omitted price bias, we examine if we need to control for demand shocks even if there is no omitted price bias (as in our case when we observe product prices and output for each firm *f* at time *t*).

Our results indicate the presence of a large amount of bias in the impact of openness to trade on firm productivity in case of a simple OLS. Our results support the use of De Loecker's (2011) methodology provided we have a good sectoral deflator which can give estimates of the deflated output to be close to the actual output. Relying on weak deflators will bias the results, particularly since they fail to consider both within and across firm price variations. Our results also stress on the need to control for demand shocks in addition to the need to control for omitted price bias. Demand shocks impact prices and reflect product quality and hence need to be considered.

Once we fully account for omitted price bias and demand shocks we get higher sectoral elasticities than compared with other specifications. A 10% reduction in tariffs increase firm level productivity by 0.81% but the impact falls to 0.23% when we accurately measure productivity and control adequately for demand shocks. The net impact of the FTA on firm level productivity drops from 7.8% to only 2.2% when we use actual productivity estimates and control for demand shocks. The FTA had the biggest productivity gain for the spinning segment which is the least protected one.

Measuring the TFP and product quality impact of the FTA: A analysis of the Pakistani firms gaining market access to China

In this chapter, we study the impact of the Free Trade Agreement on firm level productivity and quality. Much of the literature present in the trade-productivity dimension focuses on the impact of lower input tariffs and as a result on the impact of the availability of cheaper and newer intermediate inputs for production. The other side of the FTA, i.e., lower output tariffs and as a result, the impact of an increase in market access on the firm level productivity is an under researched area. Moreover, the impact of getting more market access in a developed economy (China in our case) on the productivity of firms in a developing country (Pakistan in our case) is even more limited.

Our results show that the FTA did induce firms to start exporting to China, but the net gains were small. The firms exporting to China had a moderate increase in firm productivity and quality, but they are still smaller than the gains found in literature for other developing countries. While the net gains from the FTA are small, we do however find evidence of productivity and quality gains induced from the exporting firms to the non-exporters looked in the close proximity. Particularly, being located near a high productivity upstream exporter is beneficial for a non-exporter in our case.

Overall, the results point out towards a limited benefit that exporting firms got from the FTA. Competition from the ASEAN countries and higher concessions given to them can be one of the possible explanations for this.

Measuring changes in product mix and markups as a result of the FTA: An analysis of the Pakistani firms in response to gaining market access to China

In this chapter we extend our discussion from chapter 2 and identify the sources of productivity gains. We study how firms adjust their input usage, particularly if they make any capital investments or not. We also study how firms change their product mix in response to the FTA. Finally, we study how firms' adjustment of markups, prices, and marginal cost in response to the FTA.

Results show that firms exporting to China did increase their scale (hire more materials and labor) but did not increase capital investment. Hence, we do not find any evidence of increase in investment or upgrading technology in this context. Moreover, firms which experienced productivity gains reduced the number of product varieties being manufactured. In addition to lowering their product offerings the Pakistani exporters to China were not able to decrease their marginal cost or markups. Overall, the Pakistani exporters experienced limited productivity and quality gains from the FTA. They concentered on fewer products, reduced their product scope, and increased their scale in competition with other countries in the Chinese market.

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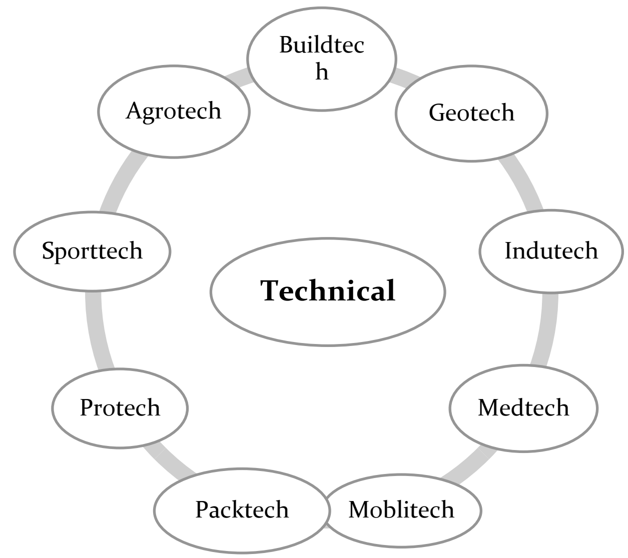
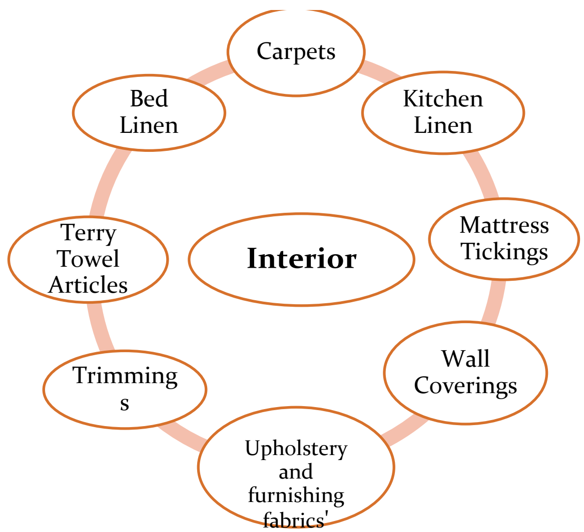
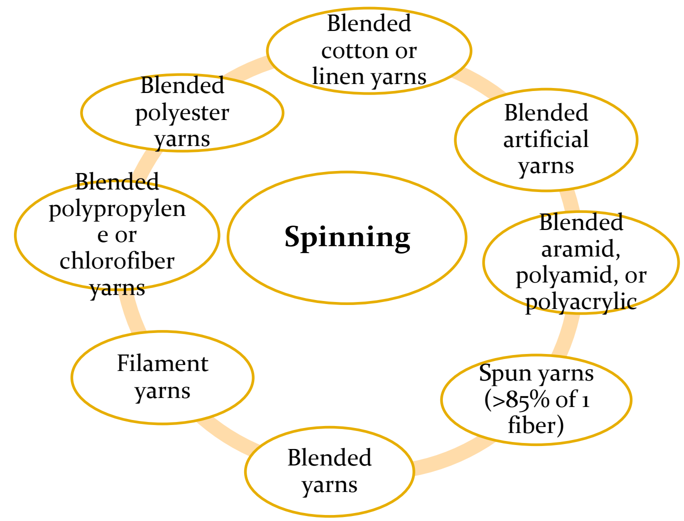
Appendices

1.1: Classification of Segments based on De Loecker (2011)




Interior
Carpets
Kitchen Linen
Mattress Tickings
Wall Coverings
Upholstery and furnishing fabrics'
Trimming s
Terry Towel Articles
Bed Linen


Spinning
Blended cotton or linen yarns
Blended artificial yarns
Blended aramid, polyamid, or polyacrylic
Spun yarns (>85% of 1 fiber)
Blended yarns
Filament yarns
Blended polypropylen e or chlorofiber yarns
Blended polyester yarns


Clothing (Fabrics and Knitwear)
Baby & children' s clothes
Accessori es
Fabrics for nightwear, outerwear, sportswear
Children's wear
Bath
Babies' wear
Women' s wear
Underwear
Stocking s, tights, socks
Rain wear, sportswe ar, & leisure
Night wear & undercloth ing
Other Fabrics
Men's wear

1.2: Results of Equation (1.20) and (1.21)

First Stage Result: Instrumenting prices by using actual tariff rates (at the product level) Dependent variable : Price	
Tariff	0.468***
	(0.8053)
F. Value of Excluded Instruments: 30.12	

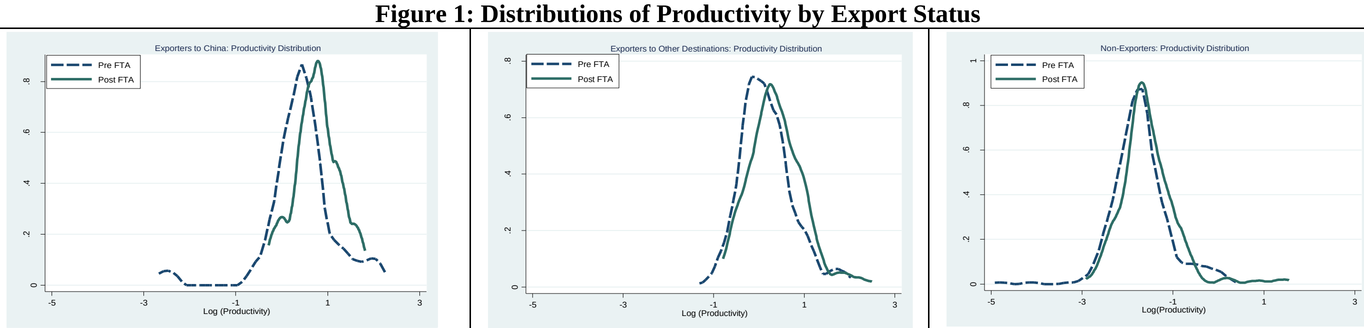
Second Stage Result: Instrumenting prices by using actual tariff rates (at the product level) Dependent variable : Output	
Prices	-2.015***
	(0.4787)

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.

2.1 Product-level Distributions of Productivity and Quality using DGKP (2016) and Khandelwal (2010) Methodologies

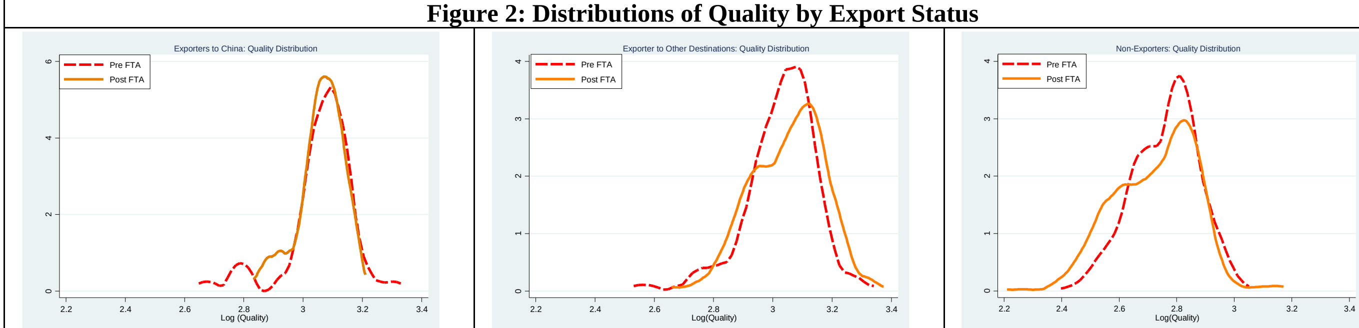
Figure 1: Distributions of Productivity by Export Status



Exporters to China	Exporters to Other Destinations	Non- Exporters

Source: Authors' Calculations based on CMI Punjab 2000-2001, 2005-06, 2010-11.

Figure 2: Distributions of Quality by Export Status



Exporters to China	Exporters to Other Destinations	Non- Exporters

Source: Authors' Calculations based on CMI Punjab 2000-2001, 2005-06, 2010-11.

2.2 First Stage Results of the Spill Over Estimation

First stage results of the Spillover analysis

Panel A: First Stage Results for Productivity: Productivity of Exporters Post FTA

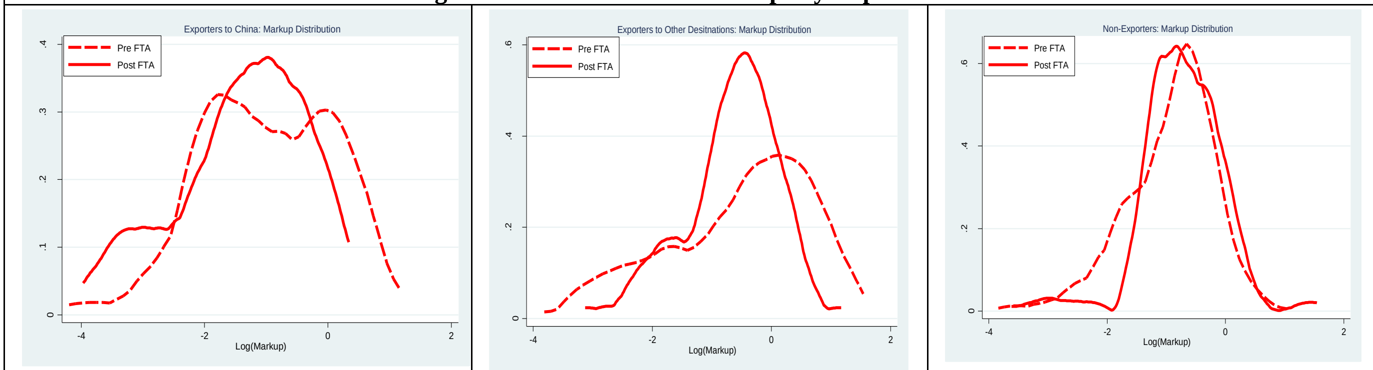
	Within 5 KM			*Within 10 KM*		
	Post FTA Productivity of Exporters classified as *Upstream Firms*	Post FTA Productivity of Exporters classified as *Downstream Firms*	Post FTA Productivity of Exporters classified as *Horizontal Level Firms*	Post FTA Productivity of Exporters classified as *Upstream Firms*	Post FTA Productivity of Exporters classified as *Downstream Firms*	Post FTA Productivity of Exporters classified as Horizontal *Level Firms*
Pre FTA-Productivity of Exporters in the same radius as the *Upstream Firms*	0.0077*** (0.0015)	-0.0064 (0.0042)	0.0000 (0.0007)	0.0023*** (0.0004)	0.0024* (0.0013)	0.0005 (0.0003)
Pre FTA-Productivity of Exporters in the same radius as the *Downstream Firms*	-0.0015 (0.0020)	0.0394*** (0.0058)	-0.0003 (0.0009)	-0.0003 (0.0003)	0.0032** (0.0010)	-0.0004 (0.0002)
Pre FTA- Productivity of firms within the same radius as the *Horizontal Level Firms*	-0.0032 (0.0032)	.0058 (0.0093)	0.0187*** (0.0015)	-0.0050** (0.0018)	-0.0093 (0.0053)	0.0043** (0.0014)

Panel B: First Stage Results for Quality: Quality of Exporters Post FTA

	Within 5 KM			Within 10 KM		
	Post FTA Quality of Exporters classified as *Upstream Firms*	Post FTA Quality of Exporters classified as *Downstream Firms*	Post FTA Quality of Exporters classified as *Horizontal Level Firms*	Post FTA Quality of Exporters classified as *Upstream Firms*	Post FTA Quality of Exporters classified as *Downstream Firms*	Post FTA Quality of Exporters classified as Horizontal *Level Firms*
Pre FTA-Quality of Exporters in the same radius as the *Upstream Firms*	0.0106*** (0.0028)	-0.0028 (0.0028)	-0.0002 (0.0009)	0.0041*** (0.0008)	0.0017** (0.0008)	0.0004 (0.0004)
Pre FTA-Quality of Exporters in the same radius as the *Downstream Firms*	0.0129*** (0.0030)	0.0241*** (0.0032)	-0.0003 (0.0010)	0.0009 (0.0006)	0.0029*** (0.0006)	-0.0005 (0.0003)
Pre FTA- Quality of firms within the same radius as the *Horizontal Level Firms*	-0.0017 (0.0051)	0.0025 (0.0051)	0.0206*** (0.0017)	-0.0089* (0.0032)	-0.0065 (0.0033)	0.0067*** (0.0016)

3.1 Product-level Distributions of Productivity, Markup, Price, Marginal Cost and Quality using DGKP (2016) Methodology

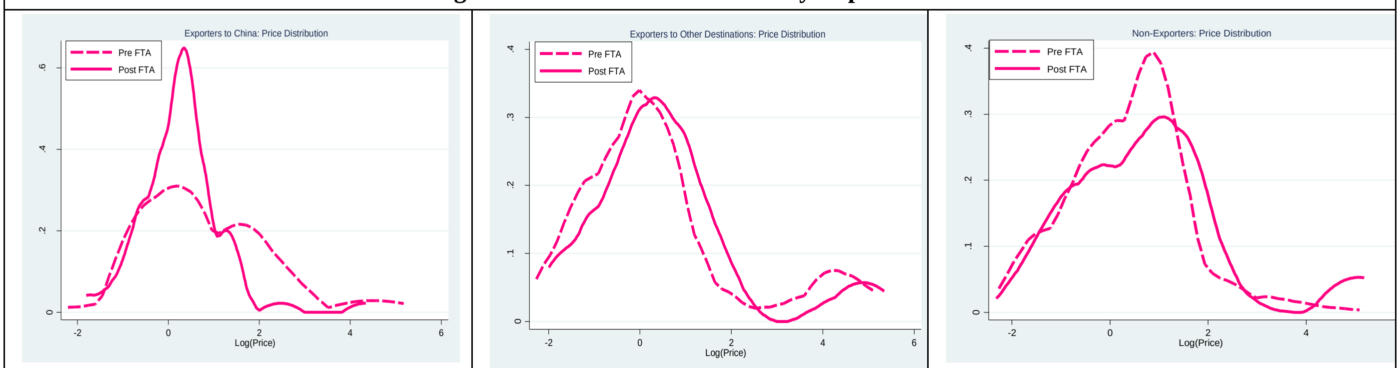
Figure 1: Distributions of Markups by Export Status



Exporters to China	Exporters to Other Destinations	Non-Exporters

Source: Authors' Calculations based on CMI Punjab 2000-2001, 2005-06, 2010-11.

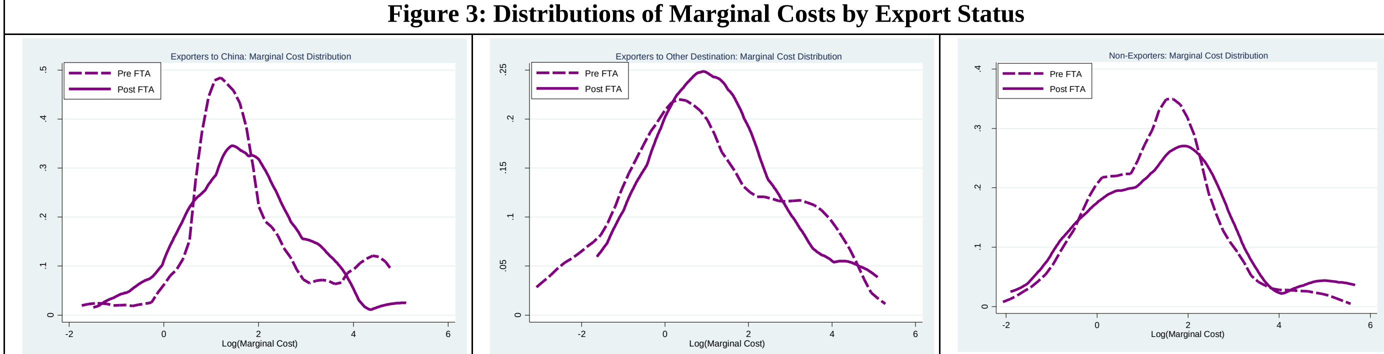
Figure 2: Distributions of Prices by Export Status



Exporters to China	Exporters to Other Destinations	Non-Exporters

Source: Authors' Calculations based on CMI Punjab 2000-2001, 2005-06, 2010-11.

Figure 3: Distributions of Marginal Costs by Export Status



Exporters to China	Exporters to Other Destinations	Non-Exporters

Source: Authors' Calculations based on CMI Punjab 2000-2001, 2005-06, 2010-11.

3.2: Impact of tariff reductions under the FTA on product level Markups. Prices and Marginal Cost using DGKP (2016)

Table 1: Impact of Pakistan-China FTA's Tariff Changes on Product-level Markup, Price and Marginal Cost in Pakistan's Textile Sector

Panel A: Impact of Tariff changes on Markup, Prices and Marginal Cost			
	Markup	*Prices*	*Marginal Cost*
	(1)	(2)	(3)
τ_{jt}	0.0151*** (0.0018)	0.0057* (0.0033)	-0.0094* (0.0037)
N	2011	2011	2011
Panel B: Impact of Tariff changes on Markup, Prices and Marginal Cost by Export Status			
	Markup	*Prices*	*Marginal Cost*
	(1)	(2)	(3)
Exporters to China*τ_{jt}	0.0882*** (0.0060)	0.1658*** (0.0103)	0.0776*** (0.0126)
Exporters to Other Destinations*τ_{jt}	-0.0029 (0.0029)	-0.0438*** (0.0050)	-0.0409*** (0.0062)
Non-Exporters*τ_{jt}	0.0145*** (0.0023)	0.0121** (0.0040)	-0.0024 (0.0049)
N	2011	2011	2011

The table presents the analysis of the impact of product level tariff changes on product level markups, prices and marginal cost. Panel A shows the results of the impact of tariffs markups, prices and marginal cost directly while panel B disaggregates the effect according to the export status of the firm. Controls include pre-FTA firm productivity, pre-FTA quality, pre-FTA number of products, and firm inputs, dummies for missing data by year, segment, year and segment-year fixed effects. In addition to this, we also control for firm-product fixed effects. Robust Standard Error in parentheses.
***, **, * significant at 1%, 5% and 10% levels of significance respectively.