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A Spatial Agglomeration Analysis of Firm Productivity: A Case of the Textile Sector of Pakistan

Muhammad Zeeshan Younas
Quaid-I-Azam University,
Islamabad Pakistan.
mzeeshan@eco.qau.edu

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Abstract: The prime objective of this study is to examine how agglomeration affects the productivity of firms by location. Using different spatial econometrics on geo-referenced data of textile manufacturers in Pakistan, the study confirmed the presence of spatial autocorrelation in firm productivity. Results show that highly productive textile firms appear to be clustered in the regions of Lahore and Faisalabad, while low productivity textile firms appear to be clustered in Karachi and the Federal areas of Pakistan. Although the spread of clusters varies a bit with the use of different weight matrices, similar hotspots and cold spot patterns are observable. Furthermore, spatial error and spatial lag models find that younger textile firms tend to be more productive than older ones and firm size, exports, quality assurance certifications, and R&D spending are the key spatial correlates of textile firm productivity.

Keywords: Firm Productivity; Agglomeration; Spatial Analysis; Textile; Pakistan.

JEL Classification: C31; C38; D22; D24; L25.

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1. Introduction

Productivity is the most fundamental determining factor of living standards. As Nobel laureate Paul Krugman (1997) famously remarked: "Productivity is not everything, but in the long run it is almost everything. A country's ability to improve its standard of living over time depends almost entirely on its ability to raise its output per worker." Productivity is recognized as a vital element of economic growth and competitiveness and understanding how to boost productivity has remained a key concern for policymakers and economists. The long-term persistence and success of a firm is dependent on the consistent increase in total factor productivity. Inquiries as to what are the determinants of firm productivity should be one of the top priorities for scholars and consultants, including policymakers, debt holders, investors, and managers. Despite an increasing body of literature on this question from different perspectives, direct comparisons of the outcomes are challenging due to differences in the theoretical frameworks, variable constructions, sample size, and research methodologies.

In recent years, several studies have suggested that those who are most productive themselves will also make others most productive in turn. In the literature, this concept is known as the spillover effect. Productivity spillovers generally refer to productivity enhancements resulting from knowledge diffusion. According to Hoekman and Javorcik (2006), these kinds of knowledge flows can be in the form of either intentional transfers or unintentional transmission. There is a strand of empirical literature available that postulates that there are several kinds of benefits an industry or a country can obtain from productivity spillovers. For instance, there is evidence that firm-level productivity increases as a result of the presence of nearby firms to which they are connected, with connectivity measured through input-output relationships, occupational similarity or patent citations (Ellison et al., 2010; Greenstone et al., 2010, Bloom et al., 2013; Faggio et al., 2017; Hanlon and Miscio, 2017). Moreover, productivity spillover benefits can also occur through workers' mobility i.e., the hiring firm benefits from the embodied knowledge and skills of incoming labor (Zucker et al. 2002; Palomeras and Melero 2010; Stoyanov and Zubanov 2014).

This study extends the previous body of literature on this subject, using a novel approach known as spatial clustering econometrics. It sheds light on the linkages between spatial agglomeration and productivity spillovers. Spatial industrial clusters have been explored by different disciplines from both theoretical and descriptive viewpoints. A prevalent explanation of the concept has been provided by Porter (1998): "a cluster is a geographic concentration of interconnected firms, associated institutions, service providers, specialized suppliers and companies in related industries". Cluster resources embody the political, institutional, cultural, social, and economic elements that can affect the internal value-creation process by clustered enterprises. Over the last few decades, a plethora of empirical literature related to industrial clusters has been developed by researchers postulating that firms can derive potential benefits from this kind of economic environment.

Productivity spillovers have also been less focused on in the firm-level literature. Certainly, the productivity of a business organization is likely encouraged by the efficiency level of other nearby organizations as spillovers in the form of better practices and knowledge transmission. In this study, we contribute to the literature by presenting empirical evidence on the firm productivity of the textile industry in Pakistan through the use of spatial econometric techniques. It enables us to take into account the fact that the productivity patterns will be dispersed not only between different kinds of textile firms but also across geographical space. If there is significant spatial autocorrelation (for instance, one object is similar to a neighboring object) in the industry then, failure to consider these may result in inference complications and biased parameter estimates.

Our analysis revolves around the textile industry of Pakistan, which has a vast influence on the economy. In March 2020, Pakistan acquired the GSP plus status extension from the European Union (EU) through 2022, granting 96% of Pakistani exports duty-free access to the EU. Ex-Advisor to then-Prime Minister Imran Khan on Commerce, Razak Dawood, suggested that this extension would help Pakistan boost its textile exports by $500 million yearly. In a modern competitive global setting, the textile industry needs to improve productivity, advance its supply chain, and maximize value addition to be able to persist. A firm-level spatial analysis can assist policymakers to articulate policies to empower the textile industry to attain global competitiveness and meet these challenges. Several countries have successfully gained competitiveness in global markets through spatial economies. For instance, the United States of America gained global competitiveness in the technological world with Silicon Valley (Sturgeon, 2003; Woodward et al., 2006; Lazarow, 2020), while China captured a big global market share of safety footwear products through spatial agglomeration of firms in Guangdong, Wenzhou and Shandong (Pattanaik & Kushwaha, 2019; Gaibor et al., 2020). Likewise, the spatial agglomeration of hi-tech firms in Bangalore, also known colloquially as the Silicon Valley of India, currently provides global software services with an annual value of approximately US$ 156.7 billion (Jain et al., 2019; Satyanarayana et al., 2022; Reserve Bank of India Press Release, 2022). Additionally, this study can help policymakers to more efficiently distribute limited industrial policy budgets: Hotspot cluster analysis can help the government to effectively distribute these subsidies according to the likelihood of productivity spillover patterns. During 2020, the federal government released PKR 47 billion to the textile sector as cash subsidies, under the Prime Minister Export Enhancement Package.

Using Pakistani textile firm-level data over the 2017-18 period, we examine the key determinants of firm productivity by using spatial econometric methods to consider productivity spillovers. The theoretical framework of the study circles around the resource-based view (RBV) of the firm. Due to spatial proximity, we confirm productivity spillovers across textile firms. Baseline results find the presence of spatial autocorrelation in our dataset, that is, positive Moran's I for the productivity variable, regardless of the weight matrix used. A consistent pattern of textile firm productivity is observed across Pakistan using different conceptualizations of spatial relationships and tools. Highly performing textile firms appear to be clustered in the Lahore and Faisalabad regions, while low-performing textile firms appear to be clustered in Karachi and the Federal areas of Pakistan. Although the spread of clusters varies slightly with the use of different weight matrices, similar hotspot and cold spot patterns are observed, robust to the conceptualization of spatial relationship or tool that is used. The regression analysis reveals that younger textile companies tend to be more productive than older ones and that firm size, exports, and R&D spending are the key determinants of textile firm productivity. Also, non-listed firms have a higher output per worker as compared to listed ones.

The remainder of the study is structured as follows: Related literature and hypotheses are discussed in the second section. Data and variables construction are presented in the third section. The fourth section defines the empirical strategy. The fifth section deals with the estimation and results. The last section concludes the study with suitable policy implications.

2. Related Literature and Hypothesis

2.1 Theoretical Framework

Heterogeneity in firm performance has significant importance in economic analysis because economic prosperity ultimately depends on the growth of firms. According to the theoretical literature, the factors that might describe a firm's performance can be categorized into three main classes: 1) market-related factors, 2) industry-related factors, and 3) firm-specific characteristics. Several attempts have been made to inspect the roles of these factors in explaining firm performance. A seminal theoretical contribution was made by Bain (1951), linking the firm performance differences to industry attributes. In fact, there are numerous theoretical viewpoints available on firm performance: the structure-conduct-performance (SCP), organization-environment-structure-performance (OESP), strategy-structure-performance (SSP), market-based-view (MBV), and resource-based-view (RBV) perspectives. Conventional techniques like MBV and SCP perspectives emphasize the role of industry characteristics in defining firm performance, while RBV highlights the significance of firm-level characteristics. Based on data availability, using spatial econometrics methods, this study is based on the RBV and emphasizes a few key variables classified by the literature as determinants of firm productivity and/or performance.

The productivity process of a firm is complex and at times idiosyncratic across circumstances and firms. Nonetheless, competitive advantage is gained when capabilities and resources are recognized as the fundamentals of continued competitive success (Locket and Thompson, 2001). Coad (2009) suggested that idiosyncratic resources are the foundation for the RBV of the firm. A question that must be asked from the perspective of jobs, firm productivity, and growth is: why do firms differ and how does it matter? The answers can be obtained from the notion that firms have differences in the ownership of technological resources and different capacities to generate and gain from productivity and knowledge transfer (Lazonick, 2005).

The RBV progressed in the 1990s, mainly based on the research of Penrose (1995), which claims that the competitive advantage of a firm is constructed on internal resources. Every firm has its own distinctive collection of resources so the RBV can be used to determine, develop, and exploit the set of opportunities. This interpretation cannot be considered as a theory of the firm behavior or structure but an effort to reveal why heterogeneity exists in the productivity of firms and how some firms gain a competitive advantage to produce supernormal profit. The uniqueness of the bundle of firms' capabilities and idiosyncratic properties are the concepts associated with the RBV of the firm. These bundles should be exclusive, non-substitutable, and rare in order to eliminate the problem of imitation by rival firms. The prime objective of the RBV is to maximize the firm's worth via optimal utilization of prevailing resources and capabilities. Locket and Thompson (2001) also point out that the RBV theory can bring many useful intuitions into firm heterogeneity and firm behavior rising from the previous amassing of resources. Another important insight animating RBV theory is that the heterogeneity across firms is based on dissimilarities in efficiency, rather than differences in market power. All things considered, it is pertinent to remember that the RBV theory concentrates on the strong association between competitive advantage and firm resources. It creates a causal ambiguity which makes it difficult for outsiders to analyze the sources of firms' success, specifically where intangible assets are concerned.

2.2 Empirical Literature

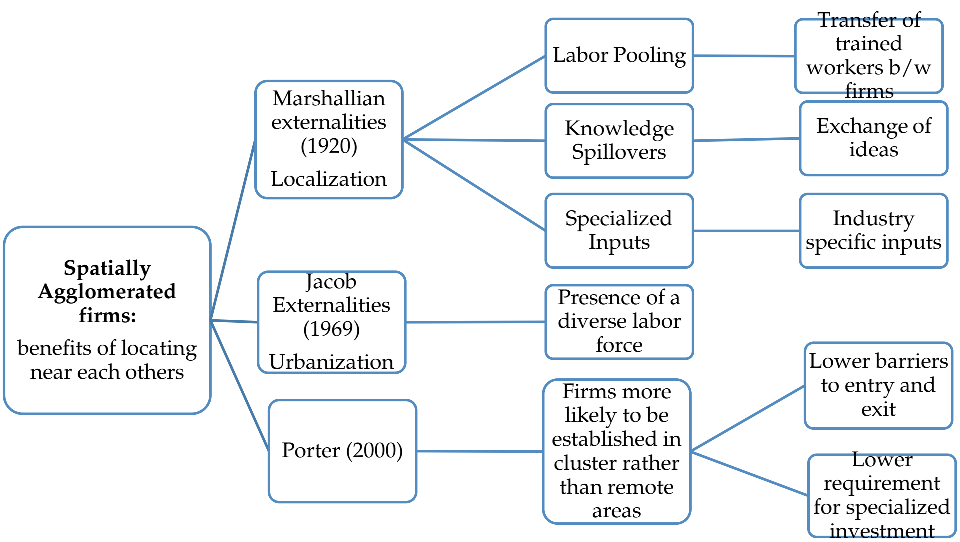
Productivity is documented as an important measure of firm performance because it reveals how effectively an organization converts inputs into outputs. Some of the regularly used productivity measures include output per worker and total factor productivity (TFP). Employment growth and firm sales in Sindh and Punjab were studied by Wadho et al., (2019). A majority of the empirical literature indicates that highly productive organizations are more likely to grow and survive, generate employment, and innovate both in developed and developing economies. In Pakistan, some recent studies revealed that productive manufacturing firms are less expected to fail (Iqbal & Siddiqi, 2013; Khan et al., 2015; Ikram & Su, 2015; Younas & Rehman, 2020). From the perspective of the Punjab province, an important contribution is made by Nasir (2017), who comprehensively examines the impact of agglomeration on firm entry and exit in a variety of industries in the Punjab. The study highlights the importance of agglomeration and concludes that the entry and exit of firms are highly associated with agglomerated industries. Similarly, Azhar and Adil (2019) examine the impacts of agglomeration on the socio-economic outcomes of Punjab and report that district-level agglomeration has positive impacts on firm efficiency and social inclusion. A recent contribution to agglomeration from Pakistan's perspective is made by Haroon & Chaudhry (2021) who mention that irrespective of firm scale, localization has a positive impact on a new firm's arrival, whereas medium and large-scale localization will have a positive connection with the scale of operation of new firms.

From a global perspective, there are several studies available that analyze agglomeration in a variety of contexts. Owoo & Naudé (2014) state that "firm productivity levels are widely dispersed across organizations, and this has begged the question why". Some of the important identified determinants of firm productivity include external shocks (Rijkers and Söderbom, 2013); firm size (Yasuda, 2005; Ito and Fukao, 2006; Cucculelli et al., 2014; Younas & Rehman, 2020); R&D (Crepon et al., 1998; Cardamone, 2017), firm age (Cucculelli et al., 2014; Younas & Rehman, 2020); education and skills of employees (Moretti, 2004); managerial competence (Mano et al., 2012) and firm exports (Wagner, 2002; Arvas & Uyar, 2014). Another strand of literature postulates that R&D, exports, and firm size have key importance in the spatial analysis of firm productivity (Cardamone, 2017). Hall et al. (2009) argue that R&D generates positive spillover effects which leads to higher productivity of firms. Baltagi et al. (2015) study the impacts of spillover from different kinds of firms like exporting and non-exporting on productivity after incorporating spatial dependence. The results conclude that firm productivity spillovers matter in the growth and survival of the firm.

Some other recent studies (Owoo & Naudé, 2014; Cardamone, 2017) report that levels of productivity are also extensively dispersed throughout space. It implies that the clustering and distance also matter i.e., the productivity of an enterprise is influenced by other enterprises in close proximity. According to Mano et al. (2012), the key reason behind this proximity impact is that "knowledge spills over quickly". Likewise, highly productive enterprises are more likely to cluster together, not only due to low-productive enterprises benefitting from horizontal linkages and from localization agglomeration like spilling over of technology and knowledge, but also because high productivity enterprises tends to push low-productive enterprises out of the market (Nichter and Goldmark, 2009; Martin et al., 2011; Bloom et al., 2013; Ali and Peerlings, 2011).

The spatial clustering of enterprises and the agglomeration benefits it confers on them have been discussed in geographical economics and regional science (Fujita et al., 1999). According to Haroon (2013), agglomeration means the "existence of diverse economic units within a similar geographical location which enables them to extract some advantage from each other's industries, for example, Hollywood in LA and computer industry in Silicon Valley". Marshall (1920) recognized three benefits/externalities that similar firms can obtain from choosing to locate in a geographically concentrated area: 1) specialized inputs, 2) knowledge spillovers, and 3) labor pooling. Jacob (1969) also underlines the advantages accruing to different sector organizations from the existence of diversified labor in an agglomerated region. Martin et al. (2011) highlight that firms clustering in close geographic proximity generate external agglomeration economies, that are localization and urbanization economies. Localization refers to a cluster of firms in the same industry while urbanization entails a diversity of different industries in the same area (Haroon, 2013; Cardamone, 2017). In this regard, several studies have dealt with developed countries and have found significant spatial autocorrelation. Figure 1 provides a visual display of the literature about benefits that firms obtain by locating near each other[1].

Figure 1 Benefits of Spatial Agglomeration



For instance, Wennberg and Lindqvist (2010) examine Swedish data and conclude that companies located in clustered zones pay higher wages, generate more employment, and survive longer. Rupasingha and Contreras (2014) analyze US data with spatial error and spatial lag specifications and contend that the observed spatial parameters are indications of spillover effects. Baumgartner et al. (2013) study the local entrepreneurial activities in Switzerland with a spatial random effect

[1] This study is based on the localization side of spatial agglomeration because the data we used here is related to textile industry only.

model and discover spillover effects. Similarly, Martin et al. (2011) study French panel data and find that clustering boosts the productivity of firms due to localization and that there are significant spatial spillover effects. Dellar (2010) uses geographical weighted regression on US microdata and finds that firms play a key role in explaining productivity in the central and eastern zones of the US.

As far as developing countries are concerned, McCormick (1999) argues that as the African continent has very weak information systems and poor infrastructure, spatial proximity would have a positive and direct influence on the productivity of African firms. Siba et al. (2012) claim that externalities and spillovers have a big influence on the performance of Ethiopian businesses. As well, Ali and Peerlings (2011) study Ethiopian handloom firms and describe that spatial clustering helps to boost firm productivity. Ayele et al. (2009) also find the presence of spillover effects among rural non-farm firms and describe that clustering helps to improve firm productivity. Additionally, Gibson and Olivia (2010) employ spatial lags and spatial error models on Indonesian firm-level data and find evidence of significant spatial autocorrelation. For Pakistan, Burki and Khan (2010), examine the spatial agglomeration of firms in Pakistan from another perspective and conclude that companies are more expected to locate in those districts where infrastructure is available in the form of resources such as skilled labor force and road density.

2.3 Research Hypothesis

Spatial autocorrelation helps to recognize the degree to which one item is analogous to other neighboring items (Owoo & Naudé, 2014). "Positive spatial autocorrelation means similar values of a variable cluster together in a map while negative spatial autocorrelation means the dissimilar values of a variable cluster together in a map" (Cardamone, 2017). In the literature, we have highlighted that firm productivity levels are extensively dispersed across space, which implies that clustering and distance also matter, that is, the productivity of an enterprise is influenced by the other enterprises in close proximity. In other words, the productivity of a company is likely encouraged by the efficiency level of other neighboring companies. Based on existing literature on spatial econometrics and firm productivity, we hypothesize that:

H1: *The productivity of a firm is highly influenced by the nearby firm productivity i.e. productivity spillovers across firms.*

H1a*: Firms with a large number of employees* (H1b*: Experienced firms,* H1c: *Exporting firms,* H1d: *Firms spend on R&D activities,* H1e: *Listed firms,* H1f: *Firms with higher ROA*) *have the propensity to co-locate to form sub-clusters within an industrial cluster.*

The linkage between productivity and firm size is well documented in the literature. RBV theory postulates a positive association between firm size and profitability because bigger organizations have better access to resources and are more expected to benefit from economies of scale that lead to higher productivity. Researchers have found different results for the association with firm size. For instance, Amato and Wilder (1985) show no relationship between firm size and productivity, and Ammar et al. (2003) report that firm profitability drops as the firm size increases; others find a negative association between size and firm productivity (Jensen & Murphy, 1990; Pi & Timme, 1993; Dhawan, 2001; Goddard et al., 2005; Yazdanfar, 2013; Wadho & Chaudhry, 2020). On the other hand, a number of studies find that firm size has a significantly positive influence on the firm productivity (Gschwandtner, 2005; Ito and Fukao, 2006; Nunes et al., 2009; Asimakopoulos et al., 2009; Stierwald, 2010; Ilaboya & Ohiokha, 2016; Medrano-Adán et al., 2019). Different scholars use different proxies to measure the firm size, for instance, total employees (Link & Scott, 2018; Younas & Rehman, 2020), total assets (Finkelstein & Hambrick, 1989; Isik et al., 2017), and sales (Lambert et al., 1991; Hill et al., 2016). Following Cole et al. (2013), the number of employees is used as a measure of firm size in our study. We argue that bigger organizations are more productive as compared to micro or medium-sized firms. Thus, we hypothesize that:

H2: *Firm size has a positive impact on firm productivity and/or performance*.

Firm age is another key determinant of productivity reported in the RBV literature (Yazdanfar, 2013). As described by Autio (2005), RBV theory states that older firms can more easily acquire resources over time because age is associated with, for example, greater access to business networks, better reputation, more information, greater experience, and more penetration with financial institutions. Curran et al. (1993) highlight that all these advantages are associated with firm age, which in turn can help an organization operate more efficiently and overcome limited access to resources. As in the literature on firm size, the existing literature on the association between firm age and firm productivity has produced a diversity of findings (Yazdanfar, 2013). Some studies (Claver et al., 2002; Wadho et al., 2019) reveal that age and firm productivity has a negative relationship, while other (Ito & Fukao, 2006; Medrano-Adán et al., 2019) describe a positive association between them. Based on this theoretical background and using log form of total years since the firm started its operation as a proxy of age, we hypothesize:

H3: *Firm age has a significantly positive impact on firm productivity.*

As mentioned in the literature, exporting firms are highly productive and larger than non-exporters (Van Biesebroeck, 2005). Bigsten & Gebreeyesus (2009) describe that, due to high competition in foreign markets, exporters are more likely to improve productivity because it enables them to exploit economies of scale. Likewise, Almeida & Fernandes (2008) mention that firms associated with international markets are more likely to obtain new technologies that play a key role in boosting firm productivity. Another important theory connected with exports and productivity relationships is the "learning by exporting hypothesis" which means firm productivity improves after entering export markets. Thus, we formulate the following hypothesis:

H4: *Propensity to export is positively associated with firm productivity.*

According to the RBV, R&D is an important resource that helps a firm to attain a competitive advantage. Hall et al. (2009) state that R&D cooperation between firms is one of the most significant factors that can enhance productivity spillovers. An important contribution by Cardamone (2017) concludes that spending on R&D activities has a significantly positive influence on the productivity of a firm. Likewise, Crepon et al. (1998), Wadho & Chaudhry (2020) and Younas & Rehman (2020) argue that spending on R&D activities has a direct effect on firm-level innovation which plays an important role in defining firm productivity. Thus, we hypothesize that:

H5: *Spending on R&D activities have a positive impact on firm productivity.*

The sample size of our study consists of both listed and non-listed textile manufacturing firms. Bennett et al. (2020) examine whether the firms listed in stock markets are more productive or not. They conclude that greater stock price informativeness has a significantly positive impact on firm productivity. To compare the productivity performance of the listed and non-listed textile organizations, we hypothesize that:

H6: *Listed textile firms are more productive as compared to non-listed textile firms.*

An important study by Jovanovic (1982) concludes that profitable organizations exploit available opportunities and efficiently utilize their resources to maximize profits. Likewise, Stierwald (2010) defines profitable companies are those that are cost-effective and more productive in their management and operations. Earlier literature has found that there is a strong association between return on assets and firm productivity. Yazdanfar (2013) provides empirical evidence that firm productivity is positively influenced by the return on assets (ROA). Based on this strand of literature, we hypothesize that:

H7: *The productivity of the firm is positively influenced by the ROA variable*.

3. Data and Descriptive Statistics

The empirical analysis of this study is based on the Survey data carried out by the Lahore University of Management Sciences (LUMS) which covers almost all kinds of manufacturing firms in Pakistan. It encompasses a wide range of topics including company name, factory plant address, year of formation, number of employees, certification information, sales performance, profitability ratios, input factor information, balance sheet, accounts section, profit & loss account, and cash flow statements. Liaqat (2013) updated this dataset for the textile industry of Pakistan and added some supplementary variables related to wages and performance measures[2]. With the help of the Pakistan Stock Exchange (PSX) Data Portal and All Pakistan Textile Mills Association (APTMA) data depository, we updated this survey for the year 2017-18 and added some new variables like ISO certifications and R&D (see Table 1 for detailed variable description). Before geo-referencing this dataset, we used Google Earth and made some changes in the addresses, to ensure the exact factory locations of textile firms. Our final sample consists of 403 listed and non-listed textile firms of Pakistan for the year 2017-18.

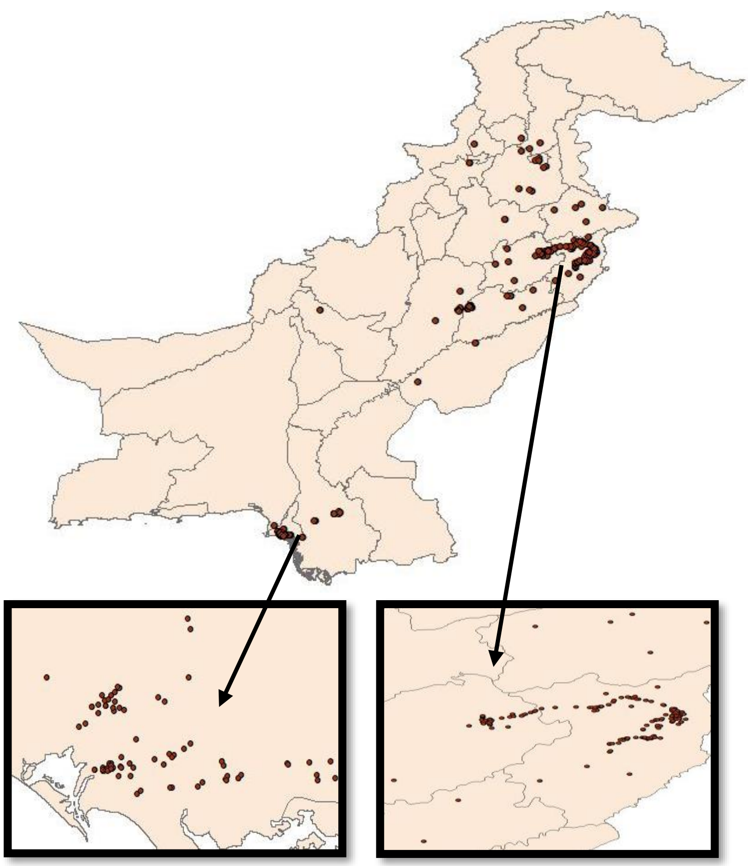
[2] We would like to thank Abid Burki from LUMS Lahore Pakistan and Zara Liaqat from University of Waterloo Canada for sharing the datasets.

Table 1: Variables Description

Name	Definition
<u>Dependent Variables</u>	
Firm Productivity	defined as the annual output per worker in the previous year
Total Factor Productivity	computed via estimating equation (11)
<u>Independent Variables</u>	
R&D	equal to one if a firm invested in internal R&D activities during the previous year, otherwise zero.
Firm Age	difference between the firms' establishment year and survey year.
Exports	The share of total output that is exported by the textile firm.
Firm Size	The study in hand uses the total full-time workers as a measure of the firm size. Following Cole et al. (2013), to capture the deep firm size impact, we divide firms into four quartiles according to the number of employees.
Small Size	First quartile of textile firms, ranging from 27 to 300 employees.
Medium Size	Second quartile of textile firms, ranging from 301 to 528 employees.
Large Size	Third quartile of textile firms, ranging from 529 to 926 employees.
Extra Large Size	Fourth quartile of textile firms, ranging from 927 to 8145 employees.
Return on Assets	a ratio of the net income to total assets and it is used to assess how profitable a textile firm is comparative to its total assets.
Listed in KSE Index	equal to one if a textile enterprise is listed in Karachi Stock Exchange (KSE) index, otherwise zero.
ISO certified	equal to one if the textile enterprise has a valid ISO certification of quality assurance, otherwise zero.
Islamabad	=1 if a firm is located in Islamabad capital territory, otherwise zero.
Balochistan	=1 if a firm is located in Balochistan province, otherwise zero.
Punjab	=1 if the firm is located in Punjab province, otherwise zero.
Sindh	=1 if the firm is located in Sindh province, otherwise zero.
KPK	=1 if the firm is located in KPK province, otherwise zero.

Tables 2 and 3 deal with the descriptive statistics and correlation analysis respectively. Thirty-one percent of textile firms invest in R&D activities while 53 percent of firms have ISO certifications in quality assurance. Additionally, 61 percent of firms are listed on the Karachi Stock Exchange and the majority of the textile firms (almost 70 percent) are located in the Punjab province. As far as firm size is concerned, 27 percent are small, 23 percent are medium-size, 25 percent are large, and 25 percent are extra-large in size. On average, a firm has 757 employees. Lastly, the correlations have the expected positive signs between firm productivity (or TFP) and R&D spending, size of the firm, quality assurance certifications, and return on assets. However, firm age has a negative relationship with firm productivity or TFP which means younger firms are more productive as compared to experienced firms. We further confirm the significance of these relationships with the help of different econometric techniques in a later section. Figure 2 defines the overall study area.

Figure 2 Total Study Area



4. Empirical Strategy

According to Tobler (1970), "The first law of geography: Everything is related to everything else, but near things are more related than distant things." The empirical strategy of this study consists of two segments: 1) exploratory spatial data analysis, and 2) regression analysis. Our analysis starts with spatial autocorrelation that helps to recognize the degree to which one item is similar to other nearby items. Positive spatial autocorrelation means similar values of a variable cluster together in a plot. To evaluate the presence of spatial dependence among the firm productivity determinants of two different firms, we use global Moran's I as a measure of spatial autocorrelation. Moran's I is a correlation coefficient that measures the overall spatial autocorrelation of the geo-referenced data set. It measures how one object is similar to others surrounding it. If objects are attracted (or repelled) by each other, it means that the observations are not independent. The following is the formula of the Global Moran Index.

$$I = \frac{N}{\sum_i \sum_j w_{ij}} \frac{\sum_i \sum_j w_{ij} w_{ij} (x_i - \mu)(x_j - \mu)}{\sum_i (x_i - \mu)^2} \tag{1}$$

Where N is the total number of firms; w_{ij} is a distance-based matrix such that $w_{ij} = 1$ if firm i and firm j are neighboring and $w_{ij} = 0$ if they are not; x_i is the attribute value of a variable at a specific location; x_j is the attribute value of a variable at another location; and μ is the mean attribute value of a specific variable. We apply this measure to firm productivity variables to examine spatial clustering, by using different types of weight matrices in an effort to impose some structure on the data. Global Moran's I help to assess the general pattern of variable distribution. Global measures provide a single value that applies to the entire dataset, or in other words, an average of the entire area. It may be more worthwhile to analyze the existence of spatial autocorrelation in firm productivity at a more localized level. A local measure calculates the value for each observation, so different patterns may occur in different parts of the region. For this purpose, we apply hotspot analysis on the firm productivity by means of different weighting matrices where hotspot means "a place with high values cluster together" and cold spot means "a place with low values cluster together". A hotspot analysis calculates Getis-OrdGi statistics for all features in the data. The estimated *z*-score highlights the locations of large and small clusters. The mapping of clusters based on the Getis-OrdGi and Kernel density function has been used to produce the desired hotspots of all values. The Getis-Ord local statistics can be written as:

$$G_i = \frac{\sum_{j=1}^{n} w_{i,j} x_j - \overline{X} \sum_{j=1}^{n} w_{i,j}}{S\sqrt{\frac{\left[n \sum_{j=1}^{n} w_{i,j}^2 - \left(\sum_{j=1}^{n} w_{i,j}\right)^2\right]}{n-1}}} \quad (2)$$

Where x_j is the attribute value for firm j; $w_{i,j}$ is the spatial weight between firm I and j; n is the total number of firms; $\overline{X}$ is the mean value and S is the standard deviation of the data as defined below:

$$\overline{X} = \frac{\sum_{j=1}^{n} x_j}{n} \text{ , and } S = \sqrt{\frac{\sum_{j=1}^{n} x_j^2}{n} - \left(\overline{X}\right)^2}$$

The G_i statistics is already in the form of a z-score, so there is no need for further manipulation. The default or recommended conceptualization of spatial relationships for the hotspot analysis tool is a fixed distance. To get a more clear and more robust picture of the methodology following Owoo and Naudé (2014), we conduct firm productivity hotspot analysis with other weighting matrices and tools such as inverse distance matrices, the zone of indifference, and optimized hotspot analysis.

For regression analysis, the spatial methodology established by Anselin (1988) is applied. Firm-level spatial autocorrelation may take two forms. First, there is a possibility of spatial dependence in the firm productivity variable, which implies that the performance of a textile sector firm may be influenced by the neighboring firm of the same sector, generating spillover effects from one point to another. The spatial lag model can take care of this possibility. Another kind of spatial autocorrelation can be due to omitted variables in the baseline model that are spatially correlated. The best choice to cope with this kind of error bias (i.e. spatial dependence in the error term) is the spatial error model. We start with the basic OLS regression model:

$$\mathrm{Y} = \mathrm{X}\beta + \varepsilon \quad (3)$$

where Y represents the dependent variable (which is firm productivity proxied by the sales per worker in our case); X is matrix of the covariates; β is the corresponding vector of coefficients, and ε is the vector of errors. To account for spatial dependency, two other models (spatial lag model and spatial error model) are employed. A standard notation of the spatial lag regression model is:

$$Y = \rho WY + X\beta + \varepsilon \tag{4}$$

where WY is the spatially lagged dependent variable and ρ is the spatial autoregressive parameter. As far as the weight matrix is concerned, the spatial inverse distance weight matrix is applied for the firm productivity analysis because it yields the most significant evidence of spatial correlation in the dataset, for instance, areas further away are constrained to matter lowest for textile firm productivity. On the other hand, a random shock to a firm in a particular location i (that is, a shock in the error term of a firm at location i) could be transmitted to other neighboring farms. In this situation, to control for the expected spatial interaction between units, a spatial error model could be applied. A standard spatial error model can be described as:

$$\begin{cases} Y = X\beta + \varepsilon \\ \varepsilon = \lambda W\varepsilon + \mu \end{cases} \tag{5}$$

where all variables are the same as defined before, except λ which is a spatial autoregressive parameter and μ is the error term vector. According to Owoo & Naudé (2014), "In the spatial error model, the error for one enumerator area is dependent on the weighted average of the errors in neighboring enumerator areas, with the strength of this relationship measured by the spatial autoregressive parameter, λ" . Additionally, we carry out a Lagrange multiplier (LM) test for both spatial lag and spatial error models to confirm whether we should adopt spatial econometric methods in our analysis or not[3]. This test provides another approach to test for likely spatial dependence in the error term. The test statistics can be described as:

$$LM = \left(\frac{1}{T}\right)\left[\frac{\acute{\varepsilon}_{OLS} W \varepsilon_{OLS}}{\sigma^2_{OLS}}\right]^2 \chi^2 \tag{6}$$

where $T = tr\left(W + \acute{W}\right)W$. LM test statistics always follow a chi-square distribution with 1 degree of freedom. A value indicates spatial dependence in the error if it is significantly different from zero. As mentioned earlier, we used sales per worker as a proxy for textile firm productivity. For robustness analysis, following Cardamone (2017), we

[3] In simple words, first we estimate our standard model with OLS estimation technique and apply LM test to check the possibility of spatial lag and spatial error models.

compute total factor productivity (TFP) as a firm performance proxy by considering a log-linear specification of a Cobb-Douglas production function with a constant return to scale:

$$ln\frac{Y_i}{L_i} = \alpha_0 + \alpha_1 ln\frac{K_i}{L_i} + \varepsilon_i \quad (7)$$

where K indicates the physical capital of the firm proxied by total fixed assets in 2017, L is the total employees of the firm in 2017, Y is the firm output in 2017 and ε is the error term of the equation. Following Marrocu et al. (2013) and Cardamone (2017), the endogeneity issue of physical capital per employee is addressed by using a GMM estimator and considering its lagged value as an instrument[4]. We can compute the *TFP* once we obtain an estimate of α_1. Rather than sales per worker, this computed *TFP* will be used as a dependent variable in our baseline model.

$$TFP_i = \exp(\ln Y_i - (1 - \widehat{\alpha_1}) \ln L_i - \widehat{\alpha_1} \ln K_i) \quad (8)$$

5. Estimations and Results

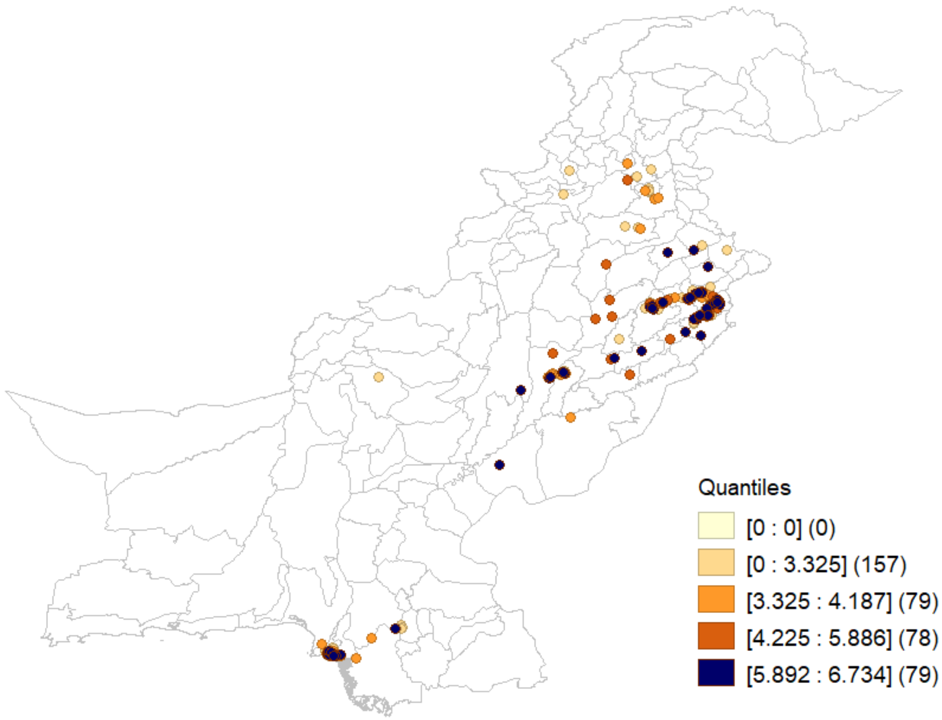
5.1 Exploratory Spatial Data Analysis

5.1.1 Quantile Map

As mentioned earlier, we measure the firm performance/productivity as sales (output) per employee in the last year. Now, using geo-referenced data, we made a quantile map depicting how firm productivity in the textile sector is distributed across Pakistan. Figure 3 provides a visual display of the quantile map -from this we can see that the textile firm productivity is highest around (the Raiwind Road area of) Lahore, Faisalabad, and the Karachi-East regions of Pakistan. Furthermore, as expected, highly productive firms appear to be clustered in space.

[4] Following Baum et al. (2007), the ivreg2 Stata command is used for the estimation.

Figure 3 Quantiles map of textile firm productivity



5.1.2 Global Moran's Indices

To find evidence of spatial clustering, Global Moran's I indices are calculated for textile firms' productivity. An essential dissimilarity between traditional and spatial statistics is that spatial statistics incorporate space and spatial connections directly into their derivation. Therefore, many of the tools in the spatial statistics toolbox need the user to pick a conceptualization of spatial relations prior to the analysis. Some general conceptualizations include inverse distance, inverse distance squared, fixed distance, the zone of indifference, *K* nearest neighbors, and contiguity. Put in another way, to impose some structure on the dataset and so correct for the observed spatial autocorrelation, we used a variety of weight matrices. The dimension of a weight matrix is 403x403 and if firm *i* and *j* are neighbors then the weight will be equal to 1, otherwise 0. "An inverse distance weight matrix allows the impact of one enumerator area's productivity on another enumerator area's productivity to decrease with distance" (Owoo and Naudé, 2014, p. 10). This weight matrix states that the close firms or neighbors have a greater impact on each other as compared to other neighbors that are more distant. On the other hand, the inverse distance squared weight matrix is similar to the previous one but has a sharper slope so that the impact drops off more speedily, and closer firms have the most impression.

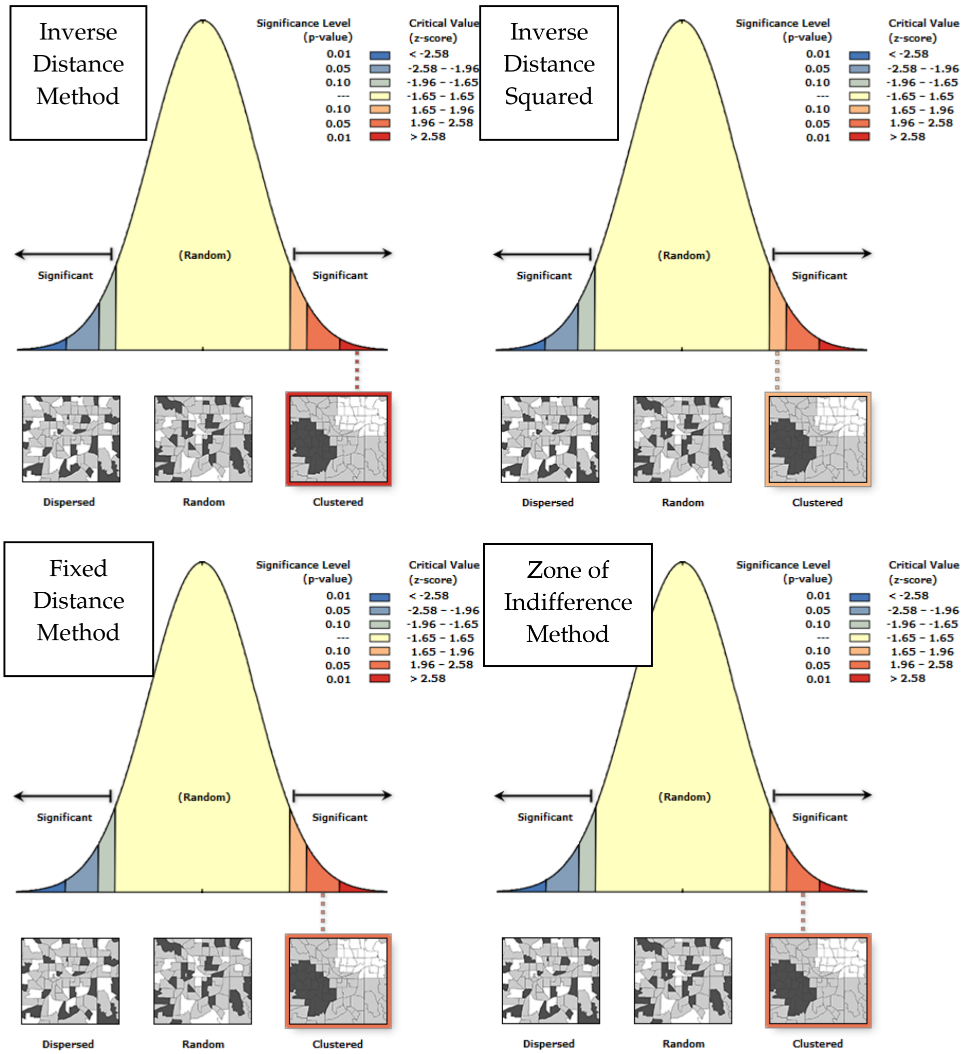
A fixed distance band is another weight matrix that we used here to examine the evidence of spatial clustering. According to this matrix, a distance band is set so that each enumerator area has at least one firm or neighbor. All enumerator areas outside this indicated critical distance are excluded from the analysis while all other enumerator areas within this distance are included. Lastly, we used the Zone of Indifference conceptualization of spatial relationships which pools the fixed distance band and inverse distance models. Features within the critical distance of a target feature are included in analyses for that feature. Aforementioned, Moran's I is a global statistical measure which use to find the spatial autocorrelation across the sample space. According to Anselin (2005), if the value of this statistic is positive then we can say that the low (high) productivity firms are surrounded by other similar low (high) productivity firms. On the other hand, if the value is negative then dissimilar firms are surrounded by each other.

Table 2: Results of Global Moran's I for textile firm productivity

Weight Matrix	Moran's I	P-Value	Z-Score
Inverse Distance	0.1207	0.0054	2.8069
Inverse Distance Squared	0.1043	0.0540	2.0302
Fixed Distance Band	0.0509	0.0224	2.2832
Zone of Indifference	0.0505	0.0170	2.4059

Table 4 provides the summary statistics of global Moran's I indices for the textile firm productivity variable. The value of Moran's I is significant and positive, no matter which kind of weighting matrix is used. These results confirm the presence of spatial autocorrelation in our dataset, so we should use spatial regression analysis to find statistically significant and unbiased coefficients (supporting our research hypothesis H1). Furthermore, Figure 4 provides the cluster distributions of firm productivity variable via using weight matrices. All four distribution graphs confirm the presence of clustering in our textile data.

Figure 4 Cluster distributions of firm productivity variable via using weight matrices



5.1.3 Hotspot Analysis

Thus far we have confirmed that our textile firm productivity dataset exhibits global spatial autocorrelation. We can also check if we check the spatial autocorrelation in firm performance at a more localized level. Different methods are available in the literature that can be used for this purpose, but we selected hotspot analysis using different kinds of weight matrices and tools. A hotspot means "a place with high values cluster together" and a cold spot means "low values cluster together". The following figures provide a clear indication of positive spatial autocorrelation in the data at a more localized level.

Red shaded clusters in Figures 5, 6, 7, and 8 depict areas where highly productive firms are surrounded by other areas with likewise highly productive firms; the darker red color means more significant clusters i.e. hotspot areas. On the other hand, blue shaded clusters in Figures 5, 6, 7, and 8 indicate areas where low-productivity firms are surrounded by other areas with similarly low-productivity firms; darker blue color means more significant clusters, i.e. cold spot areas. A consistent pattern of textile firm productivity is observed across Pakistan using the different conceptualizations of spatial relationships and tools. Highly performing textile firms appear to be clustered in the Lahore and Faisalabad regions of Pakistan, while low-performing textile firms appear to be clustered in Karachi and Federal areas of Pakistan. Although the spread of clusters varies somewhat with the use of different weight matrices, similar hotspot and cold spot patterns are clearly observable in all cases regardless of which conceptualization of spatial relationship or method is used.

Figure 5 Getis-Ord Gi* Hotspot Analysis

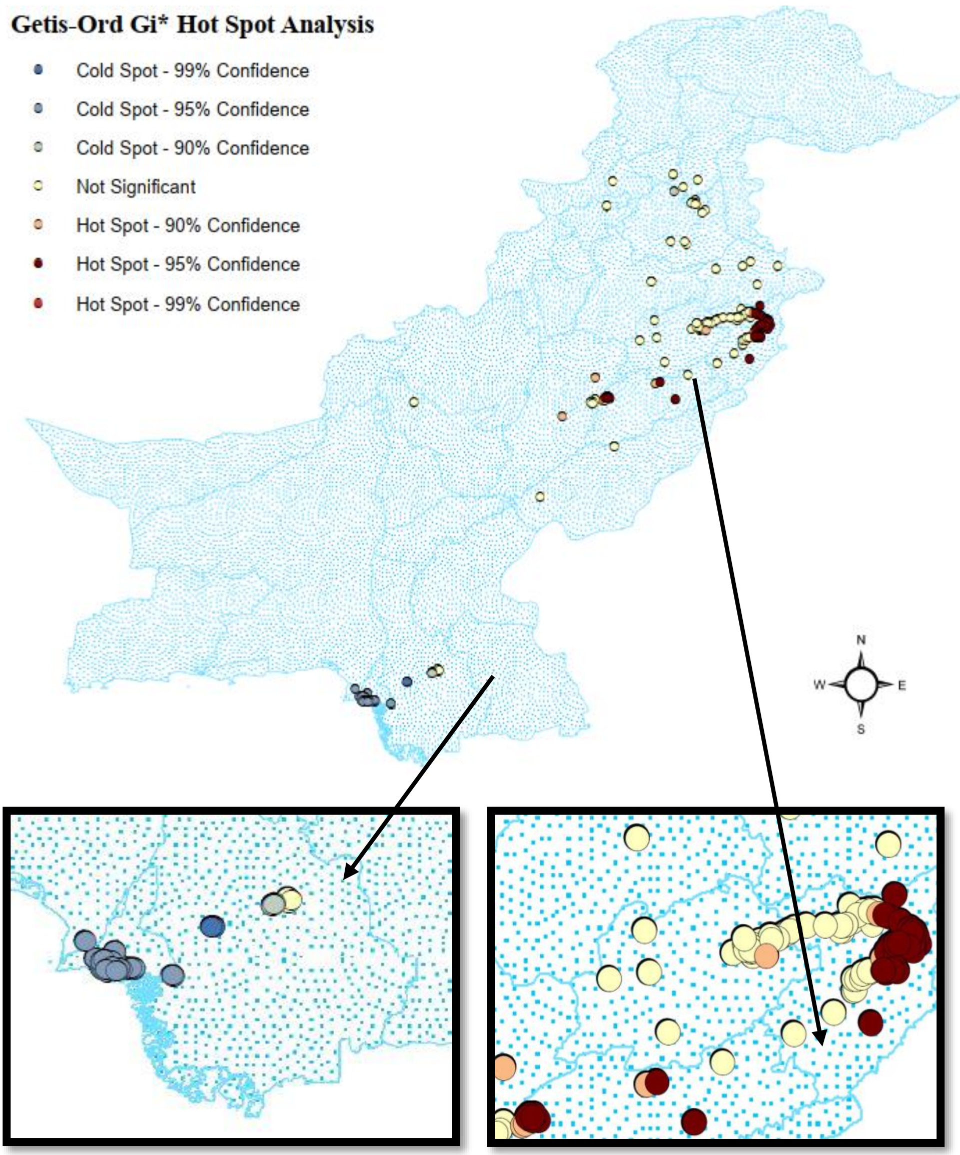


Figure 6 Optimized Hotspot Analysis

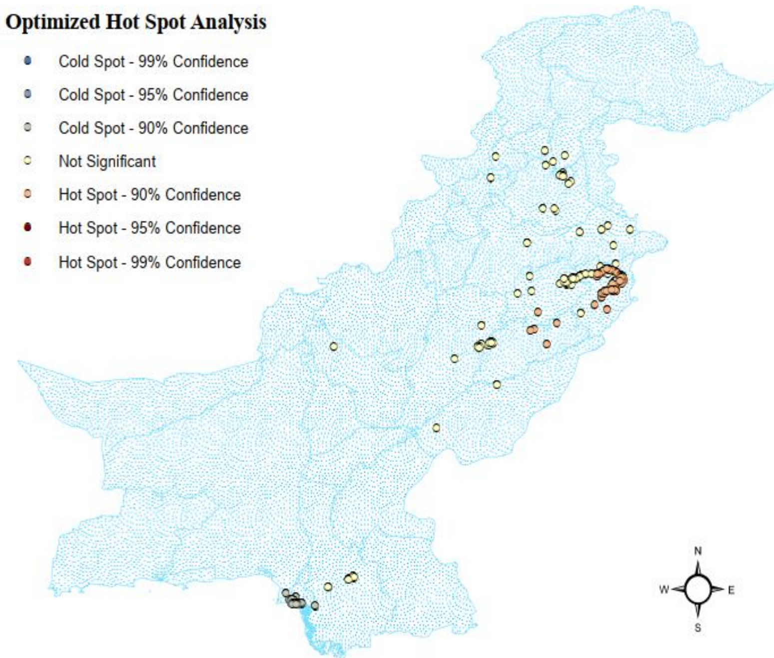


Figure 7 Fixed Distance Band Hotspot Analysis

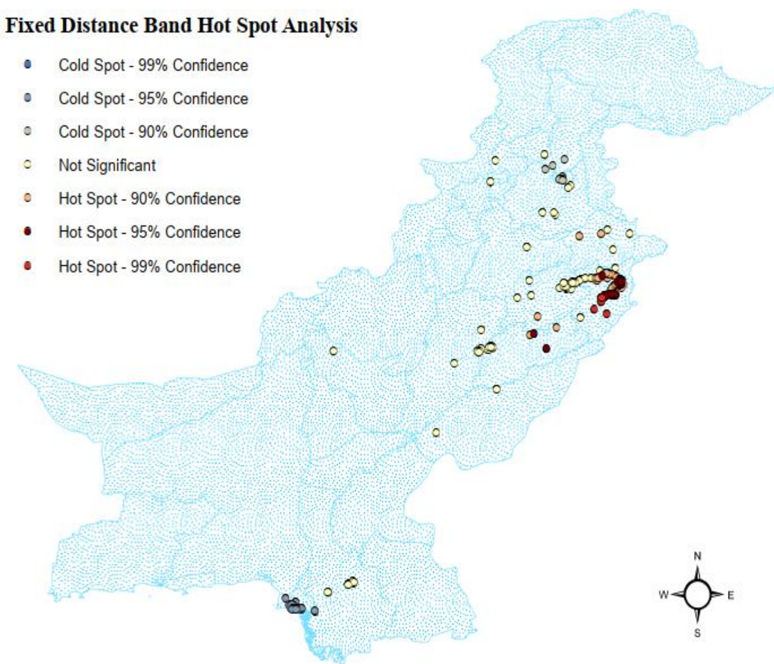
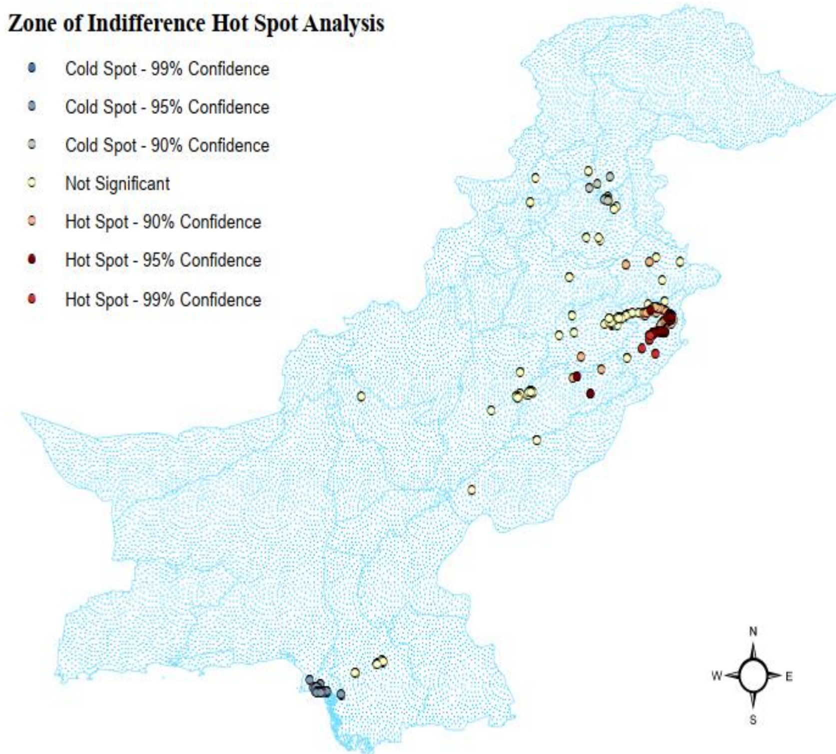


Figure 8 Zone of Indifference Hotspot Analysis



5.2 *Regression Analysis*

So far, we have shown the existence of global and local spatial autocorrelation in the firm productivity data of the textile industry of Pakistan. This raises two distinct possibilities. First, there is a possibility that some spatial dependence in the firm productivity variable is due to the influence of neighboring firm productivity. Secondly, this spatial autocorrelation can be due to omitted variable in the model that are spatially correlated. The first type can be managed with a spatial lag model while the second can be taken care of by the spatial error model. Before moving forward, following McMillan (2010) Pinkse & Slade (2010), Patridge et al. (2012) and Owoo and Naudé (2014), it is important to highlight that spatial econometrics like spatial lag models have faced some criticism in recent years. These criticisms are related to the "trouble of attaching causality to correlation patterns across space". For example, in the perspective of the present study, textile firm performance in specific spatIal locations may have identical productivity levels not due to spatial spillover effects, but as a result of some common third element. Following

Owoo and Naudé (2014), we take care to describe spatial autocorrelations as associations and to include geographic or regional zone control variables in our analysis.

Table 3 Spatial Dependence Tests

Spatial Dependence Tests	
<u>LM Tests</u>	
LM Spatial Error Model	**5.40**(0.0200)**
LM Spatial Lag Model	**4.71**(0.0300)**
<u>Moran's I Tests</u>	
Output per worker	**0.1207** (0.0054)**
Firm Age	**0.1736*** (0.000)**
Exports (log)	**0.1373** (0.0003)**
Total Employees (log)	**0.0912** (0.0160)**
Listed in KSE	**0.0886** (0.0195)**
Research & Development	**0.0633* (0.0912)**
Medium Size	**-0.0296 (0.4872)**
Large Size	**0.0266 (0.4536)**
Extra Large Size	**-0.0122 (0.8027)**
Return on Assets	**-0.0030 (0.9842)**

The inverse distance method is used for Moran's I with row standardization. Significant at ***1%, **5% and *10%. P-values are in parenthesis.

By performing LM and Moran's I tests, we now begin to examine the spatial correlations in our data. We carried out an LM test for both spatial lag and spatial error models to confirm whether we should adopt spatial econometric methods in our analysis or not. Table 5 provides the results of LM tests, we found that the p-values are lower in both cases (i.e., spatial lag model case and spatial error model case); therefore we can conclude that it is appropriate to use spatial models in our textile sector analysis[5]. This conclusion is in line with our theoretical statement that firm productivity in a particular region depends on the firm productivity in neighboring regions. This dependency does not merely relate to unmeasured variables but to an underlying spatial correlation of all variables. Furthermore, Table 5 also reports the firm-level global Moran's I value for all independent variables and control variables used in our

[5] Anselin and Rey (1991) suggest that if LM test statistics of spatial lag is higher than the LM test statistics for spatial error modes then former should be selected. However, for completeness, we estimated both spatial lag and spatial error models, results are provided in Table 3.

study. Firm age, exports, total employees, listing in the KSE, and R&D Moran's I values are all positive, with coefficient values of 0.17, 0.13, 0.09, 0.09, and 0.06, respectively (supporting our research hypothesis H1a, H1b, H1c, H1d, and H1e but rejecting H1f). Among them, firm age tends to co-locate more than other independent variables because it has the highest Moran's I (see Appendix B).

The dependent variable of our regression analysis is firm performance or firm productivity, which is proxied by output per worker (Owoo and Naudé, 2014). Following Cole et al. (2013), to capture the deep firm size impact, we divide firms into four quartiles according to the number of employees where the first quartile (smallest firms) is considered as the omitted category. Other important determinants of firm productivity include firm age, exports, listing in the KSE, R&D, and return on assets (Yazdanfar, 2013; Cardamone, 2017). In Table 6, Model 1 is non-spatial in nature and estimated by a simple OLS method, Model 2 is estimated with the spatial error technique, and Model 3 is estimated with the spatial lag technique. Finally, Models 4 and 5 are extended versions of Models 2 and 3 respectively where regional variables are introduced into the baseline model. The results of each of the specifications explain textile firms' productivity in Pakistan.

The spatial regression model results reported in Table 6 can be compared with our baseline OLS model. In general, the significance and signs of the coefficients are similar to those from the OLS estimation, and the regional variables in the extended versions of the spatial models remained statistically insignificant. Spatial and OLS results are consistent with some of our research hypotheses, such as the coefficients of export volume (supporting H4), being listed in the KSE (rejecting H6), R&D (supporting H5), large size firm, and extra-large size firm (supporting H2) are statistically significant at different levels of significance. Firm age is negatively related to firm productivity, showing that younger textile firms tend to be more productive than older ones (rejecting H3). Moreover, the results show that R&D spending by textile firms has a positive impact on firm productivity. This is in line with a strand of literature on the same subject (Matteucci & Sterlacchini, 2009; Medda & Piga, 2014; Cardamone, 2017; Younas & Rehman, 2020).

Based on the RBV, we postulated that there is a positive association between firm size and firm productivity because bigger firms have more access to resources which helps them to attain economies of scale, leading to higher output per worker. Table 6 results are consistent with this hypothesis, indicating that the large and extra-large firms have a significantly positive impact on output per worker where the extra-large coefficient is even larger in magnitude (supporting H2). Additionally, our results also confirm the hypothesis that exports have a significantly positive influence on firm productivity. However, contrary to our research hypothesis, being listed in the KSE-100 index has a significantly negative impact on productivity. In other words, textile firms listed in the Karachi Stock Exchange are performing worse as compared to non-listed textile firms. The remaining variables like return on assets (rejecting H7) and regional effect variables remained insignificant in our analysis.

Table 4: OLS and Spatial Regression Results (Dependent Variable= Output per worker)

	Model 1	Model 2	Model 3	Model 4	Model 5
	Non-Spatial	Spatial Error	Spatial Lag	Spatial Error with regional effect	Spatial Lag with regional effect
Firm Age	-0.0236***	-0.0225**	-0.0215**	-0.0231**	-0.0224**
	(0.0082)	(0.0081)	(0.0081)	(0.0083)	(0.0083)
Exports (log)	0.157***	0.151***	0.150**	0.151***	0.150***
	(0.0498)	(0.0493)	(0.0489)	(0.0494)	(0.0492)
Listed in KSE	-1.762***	-1.787***	-1.747***	-1.780***	-1.749***
	(0.2610)	(0.2560)	(0.2560)	(0.2580)	(0.2580)
R&D	0.265ᵼ	0.336ᵼ	0.284ᵼ	0.339ᵼ	0.284ᵼ
	(0.2410)	(0.2370)	(0.2360)	(0.2380)	(0.2360)
Medium Size	0.0073	0.0647	0.0151	0.0679	0.0289
	(0.2980)	(0.2940)	(0.2920)	(0.3010)	(0.3010)
Large Size	0.427*	0.355*	0.343*	0.349*	0.351*
	(0.2930)	(0.2930)	(0.2900)	(0.3010)	(0.3010)
Extra Large Size	0.632**	0.614**	0.595**	0.608**	0.604**
	(0.3230)	(0.3180)	(0.3170)	(0.3230)	(0.3250)
Return on Assets	-0.002	-0.001	-0.001	-0.001	-0.001
	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0006)
Punjab				-0.843	-0.778
				(1.4560)	(1.4670)
Sindh				-0.891	-0.752
				(1.4640)	(1.4670)
Balochistan				-0.961	-0.876
				(2.0440)	(2.0520)

	Model 1	Model 2	Model 3	Model 4	Model 5
	Non-Spatial	Spatial Error	Spatial Lag	Spatial Error with regional effect	Spatial Lag with regional effect
KPK				-0.639	-0.495
				(1.7370)	(1.7170)
Constant	4.621***	4.588***	3.917***	5.452***	4.694***
	(0.2710)	(0.2810)	(0.4100)	(1.4840)	(1.5290)
Lambda (λ)		0.218**		0.217**	
		(0.0902)		(0.0904)	
Rho (ρ)			0.192**		0.193**
			(0.0853)		(0.0866)
R-Square	0.19	0.18	0.20	0.19	0.21
Log-Likelihood		-838.15	-838.48	-837.94	-838.30
No. of Observations	403	403	403	403	403

Standard errors (SE) are in parentheses. Significant at ***1%, **5%, *10%, ˟15%.

Spatial parameters such as lambda in the spatial error model, and rho in the spatial lag model, are statistically significant and positive. The significance of coefficient lambda implies spatial dependence in unobservable firm productivity factors, while the rho coefficient shows a positive spatial dependence in productivity between firms (hypothesis H1). These results might reveal the existence of positive spillover effects[6]. In other words, the significance of the spatial lag coefficient implies some degree of interaction among textile firms in particular areas of Pakistan, while the significance of the spatial error coefficient implies that some spatially correlated omitted variables affect the textile firm productivity[7]. These results are consistent with other studies conducted for developing and developed economies (Gibson and Olivia, 2007; Baumgartner et al., 2012; Owoo and Naudé, 2014). The inclusion of regional control variables does not change the significance and magnitude of lambda and rho coefficients. The significance of lambda implies that the performance of textile firms does not change with the inclusion of regional variables, while the significance of rho indicates the presence of a diffusion process probably through information exchange or knowledge and technology transfers between textile firms in Pakistan. Furthermore, similar to R-squared, log-likelihood is a measure of the goodness of fit of a model. Table 6 reports that this value

[6] Though we have to be cautious to assign such spillover effects because of the drawbacks of spatial lag models, as discussed earlier.
[7] Significant and positive rho is a sign of expected diffusion process where firm productivity in a location predict an increased probability of identical productivity in the nearby places.

is highest in the spatial lag model as compared to the spatial error model, so we can say that spatial lag models are a better fit.

To sum up, our analysis provides some empirical evidence that the local environment has significant importance in textile firms' performance, probably probably collective learning, knowledge spillover effects, and forward and backward linkages with the local markets. Textile firms who are engaged in similar kinds of activities (like R&D and export promotion) may form a cluster to take advantage of lower energy costs, scale economies, external economies of agglomeration, and bigger markets for consumption goods and labor.

5.3 *Robustness Analysis*

To check the robustness of our findings, we use different econometric regression settings and proxies to determine the spatial determinants of firm productivity, on one hand, and to establish whether and how those changes affect firm productivity, on the other hand. These changes consist of two different settings. First, following Cardamone (2017), we replicate our baseline firm performance models (models 1 to 5) by estimating TFP as a proxy of firm performance using a log-linear specification of a Cobb-Douglas production function (see Appendix-A Table 9). In the second setting, after introducing some new explanatory variables, we re-estimate our baseline model exclusively for KSE-listed textile firms only. We introduced the earning per share variable and replaced firm size dummy variables with the log form of the total number of employees variable.

Table 5: OLS and Spatial Regression Results (Dependent Variable= TFP)

	Model 6	Model 7	Model 8	Model 9	Model 10
	Non-Spatial	**Spatial Error**	**Spatial Lag**	**Spatial Error with regional effect**	**Spatial Lag with regional effect**
Firm Age	-0.0205***	-0.0209***	-0.0205***	-0.0208***	-0.0203***
	(0.00487)	(0.00484)	(0.00483)	(0.00496)	(0.00493)
Exports (log)	0.0206	0.0186	0.0202	0.0175	0.0192
	(0.0293)	(0.0292)	(0.0291)	(0.0293)	(0.0292)
Listed in KSE	-1.741***	-1.742***	-1.739***	-1.731***	-1.729***
	(0.154)	(0.152)	(0.152)	(0.153)	(0.154)
R&D	0.226*	0.235*	0.226*	0.231*	0.222*
	(0.142)	(0.140)	(0.140)	(0.141)	(0.140)
Medium Size	-0.0179	-0.0147	-0.0188	-0.0213	-0.0261
	(0.176)	(0.174)	(0.174)	(0.178)	(0.178)

	Model 6	Model 7	Model 8	Model 9	Model 10
	Non-Spatial	**Spatial Error**	**Spatial Lag**	**Spatial Error with regional effect**	**Spatial Lag with regional effect**
Large Size	0.347**	0.351**	0.344**	0.334**	0.327**
	(0.173)	(0.172)	(0.172)	(0.178)	(0.178)
Extra Large Size	0.870***	0.872***	0.868***	0.857***	0.853***
	(0.190)	(0.188)	(0.188)	(0.193)	(0.193)
Return on Assets	0.00051	0.00042	0.00045	0.00042	0.00045
	(0.0003)	(0.0003)	(0.0004)	(0.0004)	(0.0004)
Punjab				-0.0432	-0.0295
				(0.871)	(0.872)
Sindh				-0.0785	-0.0640
				(0.872)	(0.871)
Balochistan				-0.615	-0.609
				(1.218)	(1.219)
KPK				0.0277	0.0272
				(1.025)	(1.020)
Constant	4.681***	4.687***	4.632***	4.744***	4.690***
	(0.160)	(0.161)	(0.331)	(0.887)	(0.930)
Lambda (λ)		0.0757*		0.0748*	
		(0.0910)		(0.0912)	
Rho (ρ)			0.0140*		0.00973*
			(0.0822)		(0.0849)
R Square	0.40	0.39	0.39	0.39	0.39
Log-Likelihood		-632.40	-632.73	-632.15	-632.48
No of Observations	403	403	403	403	403

SE are in parentheses. Significant at ***1%, **5%, *10%

Table 6 Results for listed firms only (Dependent Variable= Output per worker)

	Model 11	Model 12	Model 13	Model 14	Model 15
	Non-Spatial	**Spatial Error**	**Spatial Lag**	**Spatial Error with regional effect**	**Spatial Lag with regional effect**
Firm Age	-0.0273**	-0.0254**	-0.0254**	-0.0274**	-0.0273**
	(0.00859)	(0.00837)	(0.00825)	(0.00864)	(0.00851)
Exports (log)	0.138**	0.137**	0.130**	0.138**	0.132**
	(0.0487)	(0.0477)	(0.0467)	(0.0477)	(0.0469)
Research & Development	0.127	0.188	0.151	0.206	0.156
	(0.251)	(0.241)	(0.241)	(0.242)	(0.241)
Firm Size (log)	0.548*	0.485*	0.486*	0.475*	0.499*
	(0.310)	(0.297)	(0.298)	(0.302)	(0.304)
Return on Assets	-0.00028	-0.00050	-0.00042	-0.00051	-0.000440
	(0.00054)	(0.00051)	(0.00052)	(0.00051)	(0.00052)
ISO Certification	0.373	0.341	0.374*	0.368*	0.395*

	Model 11	Model 12	Model 13	Model 14	Model 15
	Non-Spatial	**Spatial Error**	**Spatial Lag**	**Spatial Error with regional effect**	**Spatial Lag with regional effect**
	(0.281)	(0.275)	(0.270)	(0.277)	(0.271)
Earnings per share	0.00308	0.00296	0.00310	0.00284	0.00286
	(0.00512)	(0.00495)	(0.00491)	(0.00495)	(0.00491)
Punjab				-0.996	-0.753
				(1.244)	(1.253)
Sindh				-0.829	-0.577
				(1.267)	(1.260)
Balochistan				-0.963	-0.729
				(1.765)	(1.766)
KPK				-0.721	-0.416
				(1.489)	(1.459)
Constant	1.653*	1.749*	0.946	2.743*	1.623
	(0.811)	(0.789)	(0.811)	(1.555)	(1.561)
Lambda (λ)		0.293**		0.298**	
		(0.0986)		(0.0992)	
Rho (ρ)			0.289**		0.294**
			(0.0942)		(0.0946)
R-Square	0.14	0.14	0.19	0.14	0.20
Log-Likelihood		-476.48	-476.48	-476.32	-476.03
No. of Observations	241	241	241	241	241

SE are in parentheses. Significant at ***1%, **5%, *10%

Table 7 reports the results of the first robustness settings where all of the coefficients of models 6-10 are consistent with the baseline models 1-5 except exports. R&D and larger firm size have a significantly positive impact on the TFP while younger firms have higher TFP as compared to the experienced ones. These and the remaining coefficients are consistent and in line with the previous literature (Matteucci & Sterlacchini, 2009; Medda & Piga, 2014; Cardamone, 2017; Younas & Rehman, 2020). Table 8 deals with the determinants of firm productivity of listed firms only, which lowers our sample size to 241 firms. All reported coefficients are consistent with the baseline models 1-5 except R&D. Newly introduced variables like ISO certification and earning per share have mixed results. Quality assurance certification has a positive impact on firm productivity in models 13, 14, and 15 while earnings per share have no significant impact on firm productivity.

To sum up the discussion, the regression analysis reveals that younger textile firms tend to be more productive than older ones and the firm size, exports, and R&D spending are key determinants of textile firm productivity. Also, the non-listed firms have a higher output per worker as compared to the listed ones. ISO certifications have a mixed impact on firm productivity while earnings per share and return on assets have no impact on firm productivity no matter which proxy is used. These findings are robust to the use of different econometric techniques and the use of different proxies.

6 Conclusion

Due to the availability of geo-referenced datasets and recent developments in econometric models, the importance of spatial analysis has significantly increased. Determinants of firm productivity have been discussed by several researchers from different perspectives and using different datasets but the presence of productivity spillovers has been understudies in the literature. The spillover impacts of better practices and knowledge transmission from more efficient firms have not been considered by the researchers, especially for developing economies like Pakistan. Certainly, the productivity of a firm is likely encouraged by the efficiency level of other nearby firms. In this study, we contribute to the literature by providing empirical evidence on firm productivity in the textile industry in Pakistan. In this study, we identify the determinants of textile firm productivity by employing spatial econometric models in which productivity spillovers across firms are taken into account. It enables us to take into consideration the fact that the productivity patterns will be dispersed not only between different kinds of textile firms but also across geographical space. If there is significant spatial autocorrelation (i.e., one object is similar to the other nearby object) in the textile industry then failure to account for this may result in inference complications and biased coefficients.

Employing spatial econometric methods, this study finds empirical evidence of productivity spillovers across textile firms in Pakistan. Baseline results confirmed the presence of spatial autocorrelation in our dataset, i.e. the value of Moran's I is positive and statistically significant for the productivity variable no matter which kind of weighting matrix is used. A consistent pattern of textile firm productivity is observed across Pakistan using different conceptualizations of spatial relationships and tools. Higher productivity textile firms appear to be clustered in Lahore and Faisalabad regions, while low productivity textile firms appear to be clustered in Karachi and Federal areas of Pakistan. Although the spread of clusters varies slightly with the use of different weight matrices, similar hotspot and cold spot patterns are clearly observable no matter which conceptualization of spatial relationship or tool is used. The regression analysis reveals that younger textile firms tend to be more productive than older ones and the firm size, exports, and R&D spending are the key determinants of textile firm productivity. Moreover, firms not listed in the stock market have a higher output per worker as compared to the listed ones. We also find that the return on assets and earnings per share have no significant impact on the performance of the textile sector but the quality assurance certificates like ISO certification have a significantly positive impact on firm productivity. To check the validity of these findings, we conducted a robustness analysis where the output per worker proxy of firm performance is replaced by the TFP of the firm and separate regression analyses are developed for the listed textile firms. The findings of these settings remain consistent with the baseline models except for the results for firms that export which are found insignificant in the case of regression on the subsample of KSE-listed textile firms.

6.1 Policy Recommendations and Limitations

Despite some limitations, it is worth stating that a major portion of the study findings is consistent with the existing literature. Also, this study is based on the novel spatial econometric methods which are recognized as a more reliable statistical techniques, strengthening our knowledge of firm productivity. The results based on these methods enable us to draw some appropriate policy conclusions. First, investment in R&D activities should be encouraged because it generates positive externalities and improves the knowledge accumulation mechanism of firms in a cluster. Second, being the most important determinant of firm productivity, policymakers should focus export oriented policies on those that promote spending in R&D. The government should provide R&D triggering subsidies to the textile sector to facilitate innovational activities, as mentioned by Crepon et al. (1998) that R&D increases firm productivity through the introduction of innovative products. Third, due to the spillover impacts of spatial clustering, our results imply that firm location plays a key role in firm productivity. So local district authorities need to attract and encourage different aspects of TFP like formulation of innovative products and/or services through R&D activities. Fourth, local government administrations should guide the neighboring organizations to specialize in a particular area and can arrange special funding for spatially proximate firms to collaborate to boost the overall productivity of a cluster. Fifth, the efficiency of a cluster depends on local firm quality. If some organizations are more efficient in a particular aspect of TFP (i.e., R&D or exports), their spillovers and knowledge sharing can strengthen the comparative advantage of the sub-cluster in that aspect of TFP. Most importantly, this study can help local industry promotion agencies to more efficiently allocate limited budgets to effectively boost clusters of firms.

Similarly, an important caveat to the findings is the limited spatial data availability which restricted us to use selective determinants of firm productivity. Another data-related limitation is not being able to lengthen the research period under steady because firm productivity may be a long-term phenomenon, i.e. performance payoffs may take longer to materialize than what can be captured by one year. Given the small sample size (403 listed and non-listed textile firms), we should be cautious about comparing these findings with other existing studies in the spatial econometric literature, since the periods, samples, and specifications are different. To better understand the spatial analysis of firm productivity, it may be worthwhile to pursue further examination with the help of broader spatial datasets. To analyze the generalization of our results it would be exciting to see if similar spatial patterns or clusters as found here apply to other manufacturing sectors of Pakistan. As our finding suggests that R&D plays a key role in boosting firm productivity, researchers should further identify what type of knowledge production is used and what kind of knowledge transfer is applied in those firms that do not invest in R&D activities but have higher TFP.

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Appendix A

Table 7 Descriptive Statistics

Variable	Obs	Mean	Std.Dev.	Min	Max
Firm Productivity	403	3.46	2.278	0.00	6.734
Total Factor Productivity	403	3.454	1.595	-2.41	6.290
No. of Employees	403	756.83	913.5	27.0	8145
Firm Age	403	26.74	15.24	1.00	70.00
Firm Size (log)	403	2.705	0.387	1.43	3.910
Return on Assets	403	-0.896	8.595	-67.5	60.50
Total Exports (log)	403	1.298	2.485	0.00	7.620
Punjab	403	0.707	0.456	0.00	1.000
Sindh	403	0.270	0.444	0.00	1.000
Balochistan	403	0.005	0.071	0.00	1.000
KPK	403	0.013	0.112	0.00	1.000
Listed in KSE	403	0.613	0.488	0.00	1.000
Research & Development	403	0.308	0.462	0.00	1.000
Small Size	403	0.270	0.444	0.00	1.000
Medium Size	403	0.232	0.422	0.00	1.000
Large Size	403	0.249	0.433	0.00	1.000
Extra Large size	403	0.249	0.433	0.00	1.000
ISO Certified	403	0.522	0.500	0.00	1.000

Table 8 Matrix of correlations

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
(1) Firm Productivity	1.00																	
(2) TFP	0.70	1.00																
(3) No. of Employees	0.04	0.08	1.00															
(4) Firm Age	-0.24	-0.33	0.24	1.00														
(5) Firm Size	0.13	0.15	0.77	0.22	1.00													
(6) Return on Assets	0.14	0.26	0.03	-0.05	-0.05	1.00												
(7) Exports	0.04	0.05	0.47	0.28	0.38	0.11	1.00											
(8) Punjab	0.13	0.18	0.06	-0.20	0.19	0.08	0.04	1.00										
(9) Sindh	-0.11	-0.15	-0.08	0.14	-0.20	-0.05	-0.03	-0.94	1.00									
(10) Balochistan	-0.04	-0.06	-0.04	0.04	-0.12	-0.22	-0.03	-0.11	-0.04	1.00								
(11) KPK	-0.03	-0.05	0.02	0.16	0.07	0.01	-0.00	-0.17	-0.07	-0.00	1.00							
(12) Listed in KSE	-0.35	-0.48	0.16	0.49	0.13	-0.12	0.40	-0.17	0.14	0.06	0.09	1.00						
(13) R&D	0.01	0.01	0.20	0.26	0.19	0.08	0.24	-0.04	0.05	-0.05	0.02	0.22	1.00					
(14) Small Size	-0.05	-0.08	-0.37	-0.13	-0.73	0.07	-0.21	-0.26	0.28	0.03	-0.06	-0.09	-0.11	1.00				
(15) Medium Size	-0.01	-0.02	-0.19	-0.16	-0.10	0.02	-0.11	0.12	-0.11	0.05	-0.06	-0.12	-0.05	-0.33	1.00			
(16) Large Size	0.03	0.05	-0.06	-0.03	0.16	-0.08	-0.06	0.12	-0.13	-0.04	0.09	-0.00	-0.06	-0.35	-0.31	1.00		
(17) Extra-large Size	0.04	0.07	0.67	0.32	0.70	-0.00	0.40	0.03	-0.04	-0.04	0.04	0.22	0.22	-0.35	-0.31	-0.33	1.00	
(18) ISO Certified	0.21	0.31	0.31	0.27	0.38	0.06	0.40	0.06	-0.08	-0.00	0.06	0.20	0.18	-0.33	-0.06	0.127	0.28	1.00

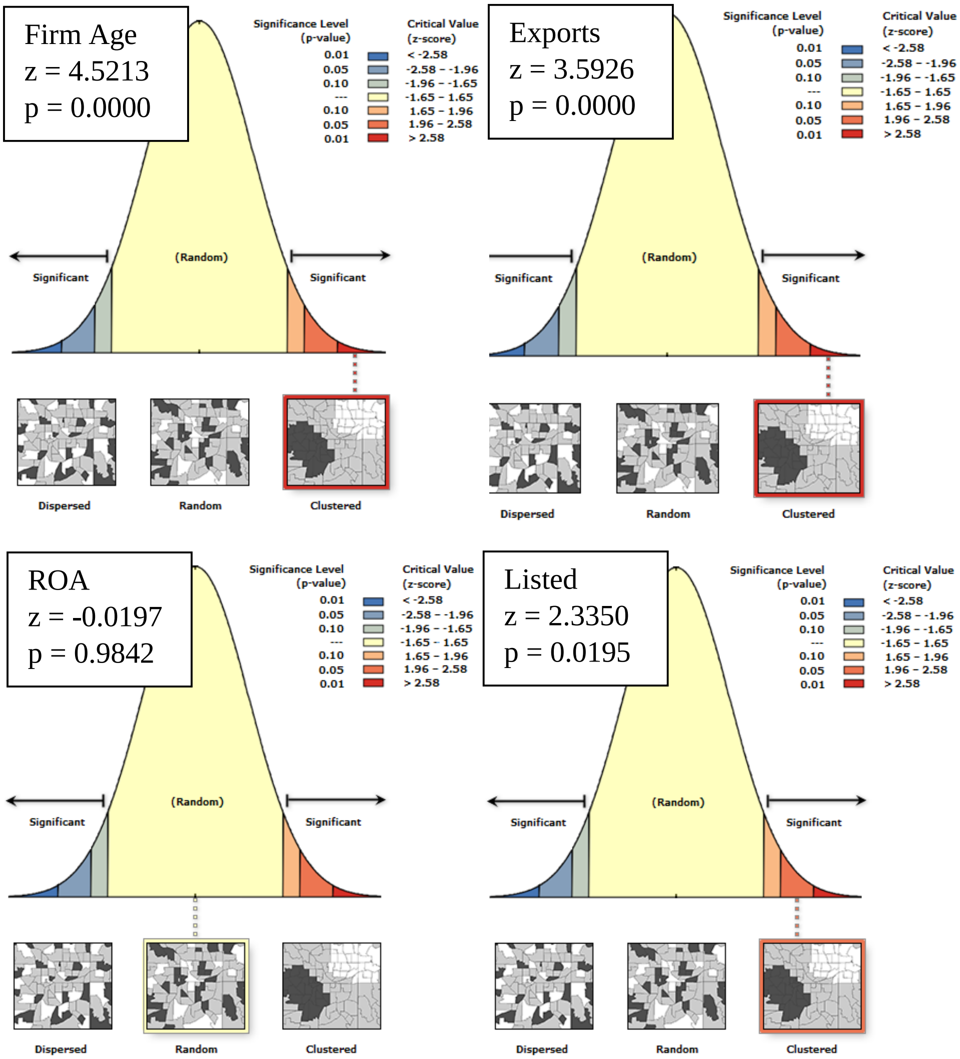
Table 9 GMM Estimates of Cobb-Douglass Production Function (Dependent Variable = Output per worker)

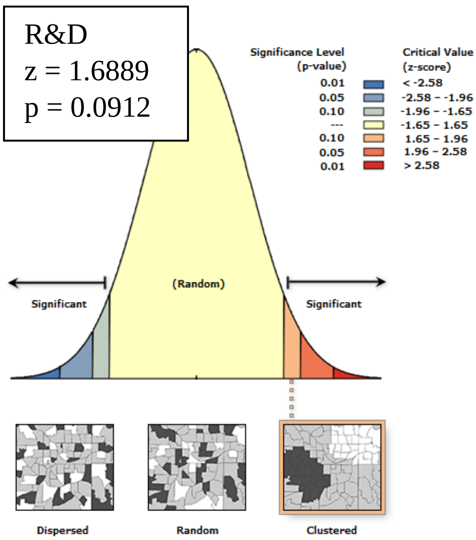
Ln (K/L)	1.2207***
	(0.0658)
Constant	-5.0994***
	(0.4688)
Centered R-squared	0.4669
Uncentered R-squared	0.8392
F-statistics	342.51
p-value	0.0000
No. of observations	403

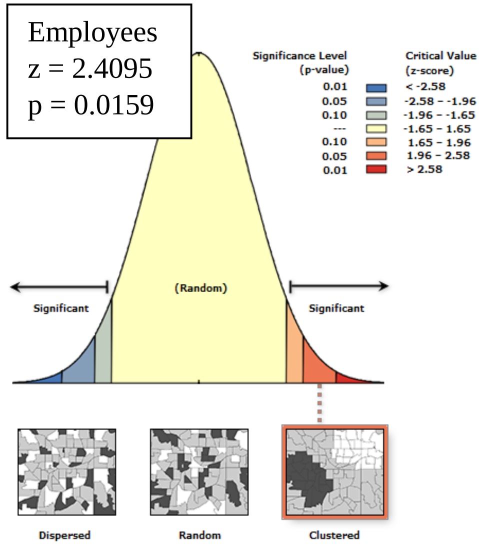
Clustered Standard errors are in parentheses. Significant at ***1%, **5%, *10%. Following Baum et al. (2007) and Cardamone (2017), estimations are carried out by using the *ivreg2* Stata command.

Appendix B

Figure: Cluster distributions of different firm variables




R&D
z = 1.6889
p = 0.0912
Significance Level
(p-value)
Critical Value
(z-score)
0.01 < -2.58
0.05 -2.58 - -1.96
0.10 -1.96 - -1.65
--- -1.65 - 1.65
0.10 1.65 - 1.96
0.05 1.96 - 2.58
0.01 > 2.58
Significant
(Random)
Significant
Dispersed
Random
Clustered


Employees
z = 2.4095
p = 0.0159
Significance Level
(p-value)
Critical Value
(z-score)
0.01 < -2.58
0.05 -2.58 - -1.96
0.10 -1.96 - -1.65
--- -1.65 - 1.65
0.10 1.65 - 1.96
0.05 1.96 - 2.58
0.01 > 2.58
Significant
(Random)
Significant
Dispersed
Random
Clustered