Impact of the Informal Economy on the Efficiency and Productivity of Pakistan's Agricultural Sector

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Abstract
According to the Ministry of Finance, more than 40 percent of Pakistan's GDP is attributed to the informal sector. Nearly 75 percent of Pakistan's working-age population is employed in the informal sector, according to the Labour Force Survey (2020-2021). The widespread persistence of the informal sector has several manifestations in the country's agricultural economy. This study analyses the impact of the informal economy on agricultural productivity in Pakistan by applying Stochastic Frontier and Principal Component Analysis models using the Pakistan Standards of Living Measurement (PSLM) farm-level data collected in 2014, 2016, and 2019. It is the first regionally and nationally representative study of the informal economy's impact on agricultural indicators using the country's largest dataset. These findings show, as prior literature has suggested, that farms utilizing formal economic relations, including better working employment contracts, more access to proper credit resources, and better irrigation systems, produce higher yields than farms that operate within informal structures. In addition, crop diversification and resource allocation were found to be significant in raising the efficiency of agriculture. But there is also a geographical dimension to productivity - some of the agro-climatic regions are lagging consistently implying a case for focused attention.

JEL Classification: Q12, Q15, C13
Keywords: Agricultural Productivity, Farm Efficiency, Cropping Patterns, Agro-climatic Zones, Crop Diversification, Informal Economy, Stochastic Frontier Analysis, Resource Allocation

Introduction

Pakistan's informal economy significantly involves the country's labor force and economic activities, particularly in agriculture. The sector shapes the livelihoods of millions of individuals. Therefore, a crucial attempt to scrutinize how the informal economy affects Pakistan's agricultural productivity and efficiency was required. This provides insights for formulating policies that foster growth and development across the country. Given that the informal economy limits access to formal credit, modern technologies, and structured labor practices, we expect that it negatively impacts agricultural productivity and efficiency in Pakistan.

Context

Approximately 80% of Pakistan's workforce is engaged in the informal economy, which encompasses a broad spectrum of economic activities ranging from small-scale farming to street vending and domestic services (International Labour Organization n.d.). A World Bank report valued the informal economy at $457 billion in 2022, accounting for 35.6% of the country's GDP-PPP level.

The majority of people live on farms, which is typical of economies relying on agriculture. There is a slight bias towards informal work in rural areas, but it accounts for almost 69% of employment in urban areas. Numerous factors can be attributed to the growth of this industry. Lack of regulation is one way in which the informal sector differs from the formal economy. In particular, agriculture is made up of a large number of unregistered businesses that also hire seasonal workers and local farmers who toil in unofficial conditions without oversight.

This widespread informality has significant effects on the region's productivity and wealth and it presents both opportunities and challenges for development initiatives meant to promote economic growth. Due to a lack of formal employment opportunities informal employment plays a crucial role in offering gainful employment in economically poor areas. This phenomenon is most evident in rural settings since the government cannot support crucial public utilities such as construction, health services, or education without experiencing a massive loss owing to unpaid taxes. This is evident in the low level of investment in modern farming techniques that reduce productivity and profitability.

These services are crucial in enhancing the production and productivity of agriculture. In addition, low pay, unreliable employment, and unfavorable working conditions are frequently associated with informal agricultural labor. As a result, the industry becomes less efficient which in turn threatens the economy's growth prospects. Barriers such as insufficient capitalization, insufficient infrastructure, and insufficient capacity building also hinder endeavors in this area. In particular and with a reference to productivity and efficiency, this paper will discuss the effects of Pakistan’s informal economy on the country’s agriculture sector.

Literature Review

Discussions on Pakistan’s agricultural productivity and efficiency often revolve around the accessibility of formal credit. In Khyber Pakhtunkhwa, the availability of formal financing significantly impacts the productivity of strawberry farmers, according to Iqbal, Niaz, & Munir (2018). Their study revealed a 15% increase in agricultural productivity for farmers with official loan access compared to those relying on informal financing. This finding aligns with numerous studies emphasizing the positive impact of formal credit on agricultural productivity. For instance, Benjamin et al. (2014) highlighted how casual agricultural businesses struggle to access programs funded through unofficial means, leading to reduced productivity. A 2021 study on cotton production in Pakistan found that farmers using formal labor contracts and financing achieved a 25% higher yield per hectare compared to those reliant on informal labor and credit sources. Additionally, the study indicated that farmers dependent on informal lending faced interest rates up to 30% higher than those obtaining formal credit, making it challenging for them to reinvest in technologies that enhance output and lower their profit margins. Mushtaq A. Khan and Abid Burki (2013) underscored the importance of credit by highlighting that companies with easier access to formal credit were more inclined to invest in technology and training, which boosts productivity and reduces inefficiencies.

The level of education attained by farmers is a crucial factor influencing agricultural productivity. Research by Saeed et al. (2021) demonstrated that farmers with a secondary education level achieved a 10% higher output compared to those with only primary education or no formal education. This trend is consistent with broader research on agriculture, linking higher education levels to increased productivity and efficiency. Educated farmers have a deeper understanding of modern agricultural technologies and methods, facilitating better farm operations optimization.

Two key elements influencing agricultural efficiency are farm size and farming experience. According to Saeed et al., farmers with more than ten years of experience outperformed their less experienced counterparts by 12% (2021). This study provides credence to the idea that seasoned farmers are better qualified to oversee farm operations effectively. However, the study did note that larger farms with lower levels of formal education might be less productive. This implies that to get the most output informal knowledge alone might not be sufficient.

The utilization of informal labor methods is a significant factor influencing productivity in Pakistan's agricultural sector. The employment of informal labor while flexible can result in inconsistent output and low quality as highlighted by research on cotton production in 2021. 70% of cotton production workers were not part of the formal labor force and their productivity decreased by 20% in comparison to formal labor practices. In formal labor contracts, there was a 25% increase in yield per hectare. Unreliable prices caused by unofficial market activity were blamed for farmers' decreased capacity to invest and unstable revenue. This also prevented farmers from investing in new technology and resulted in a 10% annual decline in average income. This finding which applies to the agriculture sector states that informal labor practices in the manufacturing sector lead to inefficiencies Mushtaq and Burki argue that formalizing labor contracts can improve both productivity and the use of available resources.

Literature highlights how resource utilization is endangered by unregulated market conditions and informal labor practices. Saeed et al. indicate that depending solely on unofficial lending channels and informal information results in increased inefficiencies. The absence of formal agreements worsened the financial instability of farmers, leading to a 15% increase in default rates in informal credit transactions. Benjamin et al. (2014) emphasize that informal agricultural enterprises limit their access to financial services and training programs by not registering or filing taxes, perpetuating inefficiencies.

Informal labor practices and unregulated markets pose a threat to resource utilization, as demonstrated by research. Saeed et al. point out that increased inefficiencies in 2021 resulted from reliance on unofficial lending channels and informal information. The 15% rise in default rates in informal credit transactions due to the absence of formal agreements further exacerbated farmers' financial instability. Benjamin et al. noted that unregistered agricultural enterprises' failure to file taxes restricts their access to financial services and training opportunities, contributing to inefficiencies. According to academic studies, extensive policy interventions are necessary to address the inefficiencies arising from the informal economy. The agriculture sector would benefit from expanded formal credit availability, improved farmer education and training programs, and the development of formal labor contracts. Additionally, implementing equitable pricing policies and regulated markets could potentially mitigate the adverse impacts of informal practices on the overall performance and productivity of this sector. Understanding labor dynamics, family size, and regional differences is essential for evaluating productivity.

Incorporating these variables into efficiency models can provide valuable insights into the factors influencing productivity and inefficiency in Pakistan's agricultural sector, especially because no prior nationally and provincially representative research of this kind has been conducted. Therefore, this paper aims to investigate how the informal economy affects productivity and efficiency in Pakistan's agricultural sector using the largest available dataset in Pakistan, the Pakistan Standards of Living Measurement (PSLM) survey.

Data and Methodology

Our data is taken from the Pakistan Standards of Living Measurement (PSLM) survey, a comprehensive regular study with economic and social indicators at the provincial and district levels, to evaluate farm production in relation to the informal economy. We analyzed farming households using data from three different years (2014, 2016, and 2019). With the use of this longitudinal technique, we could track changes and patterns in agricultural productivity and efficiency over time.

We specifically looked at the Household Integrated Income & Consumption Survey (HIICS) for these years, focusing on the farm and household portions. We compiled relevant data into the STATA software and our primary raw variables included land ownership status, total land owned, land rent, acres rented out, rent received, land value, and various costs related to agricultural operations (e.g., seeds, fertilizers, pesticides, utilities, labor, equipment rent, and other expenses). Additionally, household identifiers like province and region were also part of the dataset. Others like household asset index to get a proxy of income, government support in terms of BISP receiving, and cropping combinations, if used on the farm, were added.

We observed that a significant portion of our data had values of 0, and we addressed this by creating agro-climatic zones in our data. The zoning framework we have used in our study is based on an established classification of agro-climatic regions rooted in the work of Pickney (1989), further developed by subsequent studies, including the Asian Development Bank (2005) report. This zoning excludes Gilgit Baltistan, FATA, and AJK due to their limited agricultural practices and the unavailability of relevant data. We focus on nine distinct agro-climatic zones, which are defined as follows:

1. Other KPK
2. Low-Intensity Punjab KPK
3. Rainfed Punjab Islamabad
4. Mixed Punjab
5. Rice-Wheat Punjab
6. Cotton-Wheat Punjab
7. Rice-Other Sindh Balochistan
8. Cotton-Wheat Sindh
9. Other Balochistan

We placed districts from the PSLM dataset for three years into their respective zones. Dummy variables were created for each of these zones, labeled 1 through 9, allowing for detailed analysis across the different regions. This zoning method allows us to analyze the impacts of agro-climatic conditions on the informal economy and productivity across Pakistan's diverse agricultural landscape. A detailed listing of districts and their zonal categories can be found in Figure 1.2 of the appendix. Some districts had farms that did not report a particular input entirely so an average could not be taken, hence the zonal average was substituted. Then, we only kept entries that had cultivated land and reported harvesting crops for our analysis. This yielded 13,462 total observations. This ensured that our dataset was ready for subsequent analysis.

Equation One

$$\ln(y)=\beta 0+\beta 1\ln(x1)+\beta 2\ln(x2)+\beta 3\ln(x3)+\beta 4\ln(x4)+\beta 5\ln(x5)+\beta 6\ln(x6)+\epsilon$$

where

y is the value of production per acre (real).

x1 represents the total land under cultivation during the last Rabbi and Kharif seasons reported in acres.

x2 represents labor per acre of cultivated land. It consists of the sum of the following elements: freight, transportation, commission, insurance, storage, etc. charges, payments to permanent labor, and payments to casual and other labor.

x3 represents the cost invested in seeds/plants (including delivery charges) per acre of cultivated land.

x4 represents the cost of pesticides, chemical fertilizers, and farm yard manure (including delivery charges) per acre of cultivated land.

x5 represents the cost of utilities: water, electricity, and all other fuel charges per acre of cultivated land.

x6 represents the cost of all types of taxes, rent of equipment, animals (tractor, thresher, bullock, etc), rent paid for land during the last Rabbi and Kharif season, and any other miscellaneous expenses per acre of cultivated land.

ϵ is an error term accounting for variability in the dependent variable y.

We then logged each x variable for our log-linear analysis for the stochastic frontier. The stochastic frontier analysis (SFA) is an economic modeling method that measures the efficiency of production units, and farms in this case, by estimating the gap between observed output and the maximum possible output called the production frontier, given the set of inputs including land, labor, and fertilizers. The approach is ideal for our study to understand how much output deviation from the frontier is due to inefficiency versus random shocks or external factors.

Equation Two

$$ui = \delta 0 + \gamma 1z1 + \gamma 2z2 + \gamma 3z3 + \gamma 4z4 + \gamma 5z5 + \gamma 6z6 + \delta 1z7t1 + \delta 2z7t2 + \delta 3z7t3 + \delta 4t2 + \delta 5t3 + wi$$

where

wi is the inefficiency term, which is modeled as a function of the z variables.

z1 is a binary variable representing whether the respondent rented any agricultural land on a cash basis in the last Rabbi and Kharif season.

z2 is a dummy constructed from a continuous variable that accounts for acres of irrigated cultivated land. The dummy represents whether the respondent's land was irrigated.

z3 is a dummy constructed from a continuous variable that accounts for annual income from the Benazir Income Support Programme (BISP). Hence the dummy represents whether the respondents received BISP or not. The BISP variable itself has been used as a proxy for government subsidy.

z4 represents the number of individuals who are working as ‘family workers’, yielding total family workers per household/farm.

z5 represents the total family size per household/farm.

z6 is a dummy representing the region of the farm, rural or urban.

z71, z72, z73, and z74 are dummies generated to represent the provincial location of the farm - KPK, Punjab, Sindh, and Balochistan, respectively.

z8 is a continuous variable for the asset index. To construct the asset index, we first gathered data on key financial assets, including net savings, value of precious metals, stocks, and loans. We then collected information on various land holdings such as agricultural land, non-agricultural land, and buildings. After merging these datasets based on household identifiers, we applied Principal Component Analysis (PCA). PCA reduced the data's complexity by identifying the main components of variation. The first principal component was used to create the asset index, providing a comprehensive measure of household wealth.

Results and Discussion

After running the Stochastic Frontier, we were able to view the efficiency level for each farm. Its summary statistics for each year are displayed in Table 1, including the efficiency of the highest and lowest-performing farms.

-> year = 2014

Variable	Obs	Mean	Std. dev.	Min	Max
efficiency	4,490	.7366658	.1168753	.000023	.9476124

-> year = 2016

Variable	Obs	Mean	Std. dev.	Min	Max
efficiency	3,324	.7728129	.098837	.0000516	.9473826

-> year = 2019

Variable	Obs	Mean	Std. dev.	Min	Max
efficiency	5,648	.7541043	.1134422	.0000415	.9480948

Table 1 - Farm efficiencies for the years 2014, 2016, and 2019

Source: These statistics have been generated from the data we compiled using the PSLM dataset from years 2014, 2016, and 2019.

Efficiency

	Percentiles	Smallest		
1%	.3509277	.000023		
5%	.5265461	.0000415		
10%	.6140913	.0000458	Obs	13,462
25%	.711805	.0000516	Sum of wgt.	13,462
50%	.7804276		Mean	.7529075
		Largest	Std. dev.	.1120356
75%	.8262767	.9473826		
90%	.8581576	.9476124	Variance	.012552
95%	.8739734	.94802	Skewness	-1.878813
99%	.9059548	.9480948	Kurtosis	8.55659

Table 2: Summary statistics for overall efficiency over the three years: 2014, 2016, 2019

Source: These statistics have been generated from the data we compiled using the PSLM dataset from the years 2014, 2016, and 2019

To provide an in-depth view of how efficiency was distributed, we observed the data as provided in Tables 3, 4, and 5. For 2014, the data has a broad distribution for the observations, and the mean efficiency lies at 0.78. Negative skewness indicates that there are a significant number of observations with very low efficiency. On the other hand, the presence of high-performing farms in the top percentiles indicates the optimal use of resources. For 2016, the efficiency data shows an overall improvement in comparison to 2014. There has been an increase in mean and median efficiency scores alongside a reduction in variance, suggesting that farms are making better use of their resources. The continued presence of negative skewness suggests that the farms with low efficiency could benefit from targeted intervention. For 2019, while some entities have maintained efficiency, indicated by the stability in the 75th and 99th percentile, there has been a decline in mean and median efficiency. This suggests that some farms are encountering new problems and have failed to maintain the improvements made in the previous years.

Efficiency

	Percentiles	Smallest		
1%	.3154516	.000023		
5%	.5166641	.0000529		
10%	.5973497	.0000559	Obs	4,490
25%	.6884258	.0001127	Sum of wgt.	4,490
50%	.761897		Mean	.7366658
		Largest	Std. dev.	.1168753
75%	.8129072	.9373819		
90%	.8497123	.9416275	Variance	.0136598
95%	.8677024	.9465716	Skewness	-1.897747
99%	.9109662	.9476124	Kurtosis	9.352191

Table 3: Summary statistics for 2014

Source: Data has been self-generated in STATA using the PSLM dataset from 2014

Efficiency

	Percentiles	Smallest		
1%	.4206568	.0000516		
5%	.571726	.073893		
10%	.6490835	.1818228	Obs	3,324
25%	.738066	.183447	Sum of wgt.	3,324
50%	.7958149		Mean	.7728129
		Largest	Std. dev.	.098837
75%	.8371228	.9330864		
90%	.8663852	.934897	Variance	.0097688
95%	.881142	.9431141	Skewness	-1.911596
99%	.9060862	.9473826	Kurtosis	8.664771

Table 4: Summary statistics for 2016

Source: Data has been self-generated in STATA using the PSLM dataset from 2016

Efficiency

	Percentiles	Smallest		
1%	.3492424	.0000415		
5%	.5166441	.0000458		
10%	.6050869	.0001734	Obs	5,648
25%	.7158904	.0820836	Sum of wgt.	5,648
50%	.7851052		Mean	.7541043
		Largest	Std. dev.	.1134422
75%	.828218	.9357161		
90%	.8590165	.9375362	Variance	.0128691
95%	.872419	.94802	Skewness	-1.825903
99%	.9009422	.9480948	Kurtosis	7.559

Table 5: Summary statistics for 2019

Source: Data has been self-generated in STATA using the PSLM dataset from 2019

We now proceed to a year-wise analysis of the 20 best and worst-performing farms for 2014, 2016, and 2019 respectively, to understand what impacts efficiency so that better-informed policies can be produced.

2013-2014:

Starting with 2014, the analysis of the best-performing 20 farms reveals significant insights. We observed a diverse range of cropping patterns in these farms, 35% engaged in wheat cultivation combined with other crops, suggesting a strategy of crop diversification that helps these farms enhance soil health. In contrast, the production of sugarcane with wheat was practiced by only 20% of the farms, indicating its importance though to a lesser extent than other combinations of crops with wheat.

Investment is a critical factor that has emerged in assessing farm efficiency. 85% of the top farms invested more than the average in labor per acre, emphasizing the importance of labor management. Similarly, 65% of these farms invested above average in seeds and planting materials, prioritizing quality inputs to secure better yields. Additionally, 75% of the top farms spent more on pesticides, fertilizers, and manure, underscoring the role of advanced agronomic practices in driving efficiency. However, utilities and miscellaneous expenses, such as taxes and rent, showed more varied investment patterns, with only 50% and 35% of the top farms, respectively, spending above the average. This suggests a calculated approach to managing operational costs, potentially reflecting efficient resource allocation strategies.

Another factor that played a pivotal role in assessing the success of these farms was irrigation since a majority of high-performing farms had irrigated land which highlights the importance of water management in optimizing farm output. Interestingly, only a small fraction of these farms rented agricultural land on a cash basis or received government subsidies through the Benazir Income Support Programme (BISP), indicating a level of self-sufficiency in their operations. Family labor was utilized moderately in these farms, with only a small proportion of these farms relying heavily on family workers, suggesting that skilled labor or advanced farming techniques may be more prevalent.

Our evaluation also focused on regional variations, we observed that several efficient farms were located in Baluchistan revealing an advantage based on specific agricultural practices or regional advantages. Most of the farms are also classified as rural, emphasizing the strength of traditional agricultural practices in Pakistan’s rural areas. However, only a portion of the top farms had wealth indices above the mean measured through the asset index, suggesting that high efficiency may be more closely linked to effective management practices rather than sheer financial power.

Analyzing farms based on agro-climatic zones revealed a concentration in zone 6, where most high-performing farms were located. Based on this, we can infer that environmental conditions in Zone 6 may be particularly conducive to high agricultural efficiency, and its reasons could range from optimal soil quality to favorable weather patterns, or access to agricultural innovations and infrastructure. In contrast, no top-performing farms were found to be operating in zones 7, 8, and 9 which points to challenges within these areas, such as less favorable agricultural conditions or resource constraints that may hinder optimal farming practices.

In comparison, the analysis of the bottom 20 performing farms in 2014 presents a different picture. These farms exhibited limited cropping diversity, with few engaging in the cultivation of wheat combined with other crops. Furthermore, the absence of prominent combinations like wheat-cotton or wheat-rice suggests an underutilization of crop diversification strategies that might enhance soil health and yield stability.

These farms were found to lack investment in agricultural inputs and only a minority exceeded the mean values observed across the dataset. This is the likely cause of lower efficiency, highlighting the critical role of optimal input management in achieving higher agricultural productivity. Irrigation, which was a key factor among the top farms, was less prevalent among the bottom farms, further underscoring its importance in sustaining agricultural output.

The bottom farms also showed less engagement with formal economic practices, such as renting land on a cash basis or receiving government subsidies through BISP. The distribution of these less efficient farms across agro-climatic zones differed markedly from the top performers, with a significant number located in zone 1, which was minimally represented among the top farms. This indicates that environmental and climatic conditions in Zone 1 may be less conducive to high efficiency compared to Zone 6, where the majority of top farms are located.

2015-2016:

There are clear parallels between the top 20 performing farms in 2014 and 2016. Although wheat is the most common crop, the combination of wheat and rice is the least common; none of the top farms have this rotation. Roughly 30% of the farms mixed wheat with crops other than rice. This widely used combination of wheat and other crops highlights the strategic diversification found in the most productive operations. It is interesting to note that among the best performers, wheat-sugarcane and wheat-cotton farming is still quite low, supporting the hypothesis that these combination crops might not be grown in the most effective ways at the moment.

A review of the top 20 farms shows notable inefficiencies, including a deficiency in crucial inputs like labor and irrigation, and a conspicuous lack of crop variety. These farms typically concentrate on growing a single crop, which may lead to decreased soil health and productivity overall. The top farmers' average cultivated land in 2016 was 16.63 acres, which was more than the 6.030667 average. But just like in 2014, it seems that intensive management techniques have a greater influence on farm efficiency than just the amount of land used. Merely 25% of the most successful farms surpassed the mean land area, suggesting that meticulous land management remains a critical component.

As with the results from 2014, the best farms made significant investments in labor, fertilizers, and seed. The fact that 35% of the best farms spent more than average on these inputs highlights the continued significance of superior resources in attaining efficiency. A noteworthy observation is that 25% of the top farms used more pesticides than average indicating how crucial pest management is to maintaining high productivity. Roughly 15% of the top farms reported higher-than-average miscellaneous expenses which were likely related to purchases of equipment and infrastructure. This pattern aligns with the 2014 data which demonstrates that the most productive farms continuously make infrastructural investments to maintain high operational standards.

As of 2014, the majority of the top farms had either non-cash rental agreements or owned their land providing them with a stable operating base. 95% of the top farms had irrigated land which is a little more than in 2014 and shows how important irrigation is still. The continued emphasis on irrigation shows how crucial it is to sustain consistent crop growth and yield.

2016 saw a decrease in the number of top farmers utilizing BISP compared to 2014. This suggests that although assistance of this kind is beneficial it still constitutes a minor part of the most efficient operations. A preference for outside labor sources was evident in the fact that only 40% of the top farms heavily relied on family labor. There has been a little shift in the regional distribution of top farms, with more representation from Punjab and Balochistan, and a slight reduction from KPK. This may point to changing advantages or difficulties specific to the area.

Based on 2016 data, zones 1 (Other KPK) and 9 (Other Balochistan) continue to have a high concentration of top farms; 12 of the top 20 farms are found in these zones. This confirms the 2014 research's findings that these zones provide the best circumstances for highly productive farming. Zones 3, 4, and 5, on the other hand, are still under-represented, which suggests that these places continue to have difficulties, perhaps as a result of harsher weather or less favorable economic environments.

The bottom 20 farms in 2016 are distinguished by low levels of crop diversification and lower land use—the average amount of cultivated land is 6.5 acres—and significantly lower investments in land improvement or essential inputs like labor and irrigation. The inefficiency of these farms can be attributed to their frequent use of single-crop systems which can deteriorate the soil and reduce yields. Regarding the wheat-rice cropping pattern, only one farm displayed a positive value. Zone 2 is where the majority of these are located (Low-Intensity Punjab KPK). A significant distinction between the best farms and others is the absence of investment in cutting-edge farming methods and facilities.

2018-2019:

The top 20 performing farms in 2019 continue to exhibit patterns consistent with those seen in previous years, particularly in terms of crop selection and investment behaviors. Wheat remains a staple crop, with around 40% of the top farms using a wheat-rice combination. This combination remains a common practice among the most efficient farms, likely due to its beneficial effects on soil fertility and pest management. Additionally, wheat paired with other crops, such as maize or barley, was noted in the same percentage of the top farms, suggesting a continued focus on crop diversification to optimize land use. The bottom twenty performing farms in 2019 share several characteristics that differentiate them from the top performers. A notable lack of diversification is observed, with most of these farms focusing on single crops. This approach likely contributes to lower soil fertility and overall inefficiency. Moreover, these farms invested significantly less in labor, irrigation, and high-quality inputs, which may explain their lower performance.

At 8.29 acres, the average cultivated land among the top farms in 2019 was marginally more than in prior years. But as previously seen, efficiency appears to be more dependent on the level of management than land area. Only 10% of these top farms exceeded the average land size, reinforcing the idea that intensive, rather than extensive, farming practices are key to high efficiency. The best farms in 2019 made significant investments in labor, seeds, and fertilizers. The fact that 90% of the best farms spent more on these essential inputs than the national average highlights how important high-quality resources are to attaining high output. It is worth noting that 70% of top farms also made utilities and pesticide investments, underscoring the growing significance of these elements in sustaining productive farm operations.

Most of the top farms in 2019 had non-cash rental agreements or owned their land, similar to prior years, suggesting a stable and possibly less risky operating environment. 90% of the top farms have irrigated land, demonstrating the continued importance of irrigation. This enduring pattern shows how important water management is to attaining high farm productivity. Only 5% of the top farms were found to be using the Benazir Income Support Programme (BISP), indicating that although it is not a significant factor, government support can help improve farm efficiency. The regional distribution revealed a steady presence of top farms in Punjab and Balochistan, with a minor increase in top farms in KPK, suggesting possible advancements in farming in this region.

Based on the 2019 statistics, it is evident that the top farms are still concentrated in Zones 1 (Other KPK) and 5 (Rice-Wheat Punjab), home to 12 of the top 20 farms. Zones 7 and 8 are still underrepresented among the top farms, indicating continuing issues that could impair productivity, like more extreme weather or unfavorable economic situations.

The bottom 20 farms in 2019 exhibit limited crop diversity, with the majority growing between zero and two crops. Notably, none of these farms followed a wheat-cotton, wheat-rice, or wheat-sugarcane cropping pattern, with only four farms growing a combination involving wheat and other crops. These farms generally demonstrate lower productivity, reflected by the modest average cultivated land size and relatively low input investments.

The 2019 analysis supports the patterns observed in previous years, emphasizing the value of meticulous land management, well-planned crop combinations, and substantial expenditures on superior inputs and infrastructure. The best farms are still performing well in regions with good agricultural conditions, such as Punjab and Balochistan, while the bottom farms are inefficient due to poor management practices and a lack of diversification. These findings suggest that targeted interventions that support improved farm management practices and diversity may help to raise efficiency in all areas.

Limitations

The research paper has certain limitations. First, the dataset covers only three non-consecutive years, limiting our ability to observe long-term trends and potentially overlooking the effects of certain policy changes or external factors. Secondly, before analysis, a large number of missing values in the dataset were substituted with mean values. Even though it is required, this method could skew the data in favor of the average and hide more subtle findings.

We encounter difficulties with the variables as well. The influence of government support on agriculture may not be fully captured by using BISP as a proxy in the lack of a clear metric for subsidies. We are also limited in our research of the impact that formal credit plays in improving efficiency because there are no variables to quantify access to this important element in agricultural output. Lastly, there are no statistics on weather patterns or associated details provided by the PSLM study. Even though we established zones per national weather trends, this presents a challenge when assessing the agricultural industry, as the weather has a substantial impact on productivity.

Conclusion and Policy Implications

Policy Recommendations

To enhance agricultural efficiency and productivity, several targeted policy recommendations are proposed. First, government-supported programs should promote crop diversification by providing subsidies for diverse, high-value crops and educational initiatives on benefits like improved soil health. Investing in water management infrastructure, such as drip irrigation systems financed through low-interest loans, will ensure reliable water sources, boost crop yields, and stabilize farm output in water-scarce areas.

Encouraging cropping pattern diversification can improve outcomes, especially by avoiding monoculture systems like the wheat-rice combination. Tax breaks or subsidies should incentivize farms to plant varied crops that enhance soil health. Effective land management is crucial; government extension services should offer resources for precision farming and crop rotation, and provide financial assistance to optimize land use.

Investing in infrastructure and inputs is vital. Improving supply chains, establishing bulk purchase programs, and offering subsidized credit for high-quality seeds and fertilizers will boost productivity. Prioritizing rural infrastructure projects, such as storage facilities, is essential. Promoting mechanization through low-interest loans and subsidies will also increase yields and input efficiency.

Restructuring land ownership and tenure systems is necessary to enhance productivity. Stable land tenure and favorable rental arrangements are vital, alongside implementing land reforms to support formal land markets and resolve disputes. Upgrading irrigation infrastructure and facilitating access to government assistance programs, like BISP, are also critical.

Regional development initiatives should focus on research, extension services, and infrastructure to address local challenges. Improving agricultural extension services will help disseminate modern farming techniques and sustainable practices. Lastly, formalizing the informal economy by promoting formal financial services and labor registration can help farmers transition to formal markets, improving overall sector efficiency.

Way Forward

Future research ought to set an emphasis on longitudinal studies that monitor the effects of market and agricultural policy changes over time on farm efficiency, to increase agricultural output and deepen our understanding of the subject. A better perspective can also be achieved by integrating qualitative information from farmer interviews with quantitative data. Lastly, evaluating the success of current agricultural policies will provide information on their real-world effects, directing the creation and modification of new policies in the future.

Conclusion

This research analyses the effect of the informal economy on Pakistan's agricultural sector efficiency and productivity. To achieve these objectives, the study has used nationally and regionally representative data from the PSLM survey and applied methodologies like Stochastic Frontier Analysis and Principal Component Analysis. Such analytical observations show that issues of informality in the land, labor, and credit markets imply adverse impacts on productivity and cost recovery particularly in areas with limited adoption of these technologies and physical modalities.

The study supports our hypothesis that informality yields lower productivity in the agricultural sector while access to capital and modern innovative agricultural technologies, as well as crop management techniques, yield noticeably higher performance. Despite its limitations, including gaps in longitudinal data and incomplete variables for government support and credit access, the research underscores the urgent need to address the structural inefficiencies in the agricultural sector caused by informality. Policymakers must focus on initiatives such as formalizing the agricultural economy, enhancing access to credit and subsidies, improving rural infrastructure, and promoting sustainable farming practices.

In conclusion, the findings of this study call for a holistic approach to reforming Pakistan's agricultural sector. By addressing the inefficiencies perpetuated by informality, fostering regional equity, and equipping farmers with the tools and knowledge needed to optimize productivity, Pakistan can significantly enhance its agricultural output and contribute to broader economic development.

Appendix

Exhibit A1 - Summary Statistics for Dataset

	(1)	**(2)**	**(3)**	**(4)**	**(5)**
VARIABLES	**N**	**mean**	**sd**	**min**	**max**
wheat_rice	13,462	0.252	0.434	0	1
sugarcane	13,462	0.239	0.426	0	1
wheat_other	13,462	0.561	0.496	0	1
crop_num	13,462	2.735	1.260	0	8
x1	13,462	5.611	9.918	1	322.5
x2	13,462	4,823	7,128	32.25	192,000
x3	13,462	3,964	4,210	28.45	136,542

x4	13,462	9,304	8,194	60	221,881
x5	13,462	5,185	5,759	41.67	81,925
x6	13,462	8,981	15,334	21.50	833,333
y	13,462	69,644	58,747	1	1.451e+06
zone	13,462	4.975	2.684	1	9
id	13,462	6,732	3,886	1	13,462
t	13,462	2.086	0.864	1	3
ln_y	13,462	10.90	0.808	0	14.19
ln_x1	13,462	1.224	0.935	0	5.776
ln_x2	13,462	6.154	3.352	0	12.17
ln_x3	13,462	7.745	1.560	0	11.82
ln_x4	13,462	8.548	1.805	0	12.31
ln_x5	13,462	4.596	4.164	0	11.31
t1	13,462	1.086	0.864	0	2
ln_x6	13,462	8.356	1.689	0	13.63
z1	13,462	0.134	0.341	0	1
z2	13,462	0.816	0.388	0	1
z3	13,462	0.138	0.345	0	1
z4	13,462	1.085	1.378	0	20
z5	13,462	7.482	3.629	1	55
z6	13,462	0.928	0.258	0	1
z71	13,462	0.196	0.397	0	1
z72	13,462	0.453	0.498	0	1
z73	13,462	0.271	0.445	0	1
z74	13,462	0.0802	0.272	0	1
t_2	13,462	0.247	0.431	0	1
t_3	13,462	0.420	0.494	0	1

z8	13,462	-0.0696	0.830	-4.014	25.89
efficiency	13,462	0.753	0.112	2.30e-05	0.948

Source: Data has been self-generated in STATA using the PSLM dataset from years 2014, 2016, and 2019.

Exhibit A2 - Districts Classification into Zones

Zone	**Districts Within Zone**
1 Other KPK	Chitral, Upper Dir, Lower Dir, Swat, Shangla, Bonair (Buner), Malakand, Kohistan, Mansehra (Mansehra), Batagram, Abbottabad, Haripur, Tor Garh (Tor Ghar), Mardan, Swabi, Charsada (Charsadda), Peshawar, Nowsehra (Nowshera), Kohat, Hangu, Karak, Bannu, Lakki Marwat, Tank, Bajur, Khyber, Mohmand, Kurram, Orakzai, South Waziristan
2 Low-Intensity Punjab-KPK	D. I. Khan (Dera Ismail Khan), Bhakhar (Bhakkar), Mianwali, D. G. Khan (Dera Ghazi Khan), Rajanpur, Layyah, Muzaffar Garh (Muzaffargarh)
3 Rain-Fed Punjab-Islamabad	Attock, Rawalpindi, Jehlum, Chakwal, Islamabad
4 Mixed Punjab	Sargodha, Khushab, Faisalabad, Chiniot, Jhang, T.T. Singh (Toba Tek Singh), Okara
5 Rice-Wheat Punjab	Gujranwala, Hafizabad, Gujrat, Mandi Bahuddin, Sialkot, Narowal, Lahore, Kasur, Sheikhupura, Nankana Sahib
6 Cotton-Wheat Punjab	Sahiwal, Pakpattan, Vehari, Multan, Lodhran, Khanewal, Bahawalpur, Bahawalnagar, Rahim Yar Khan
7 Rice-Other Sindh-Balochistan	Jacobabad, Kashmore, Shikarpur, Larkana, Shahdadkot, Dadu, Jamshoro,

	Badin, Thatta, Sujawal (Sijawal), Karachi Central
8 Cotton-Wheat Sindh	Sukkur, Ghotki, Khairpur, Nowshero Feroze, Nawabshah, Hyderabad, Tando Allah Yar, Tando Muhammad Khan, Matiari, Sanghar, Mir Pur Khas (Mirpurkhas), Umer Kot (Umerkot), Tharparkar, Malir, Shaheed Benazirabad
9 Other Balochistan	Nushki, Sherani, Quetta, Pishine (Pishin), Qilla Abdullah, Loralai, Barkhan, Musa Khel (Musakhel), Kalat, Qilla Saifullah, Zhob, Sibbi (Sibi), Ziarat, Dera Bugti, Bolan/ Kachhi (Kachhi), Jaffarabad, Nasirabad/ Tamboo (Nasirabad), Jhal Magsi, Lasbela, Lehri, Panjgur, Sohbatpur

Source: 'Assessment of Farmers' Vulnerability to Climate Change in Agro-Climatic Zones of Pakistan: An Index-Based Approach

Exhibit A3 - Statistics for Farms

Category	**Top Performing 20 Farms (2014)**	**Bottom Performing 20 Farms (2014)**
Cropping Patterns		
Wheat-Cotton	4 farms	0 farms
Wheat-Rice	2 farms	0 farms
Wheat-Sugarcane	4 farms	0 farms
Wheat-other	7 farms	2 farms
Crop number	1-5	0-2
X Variables		
X1 (Mean: 6.761)	6 farms above mean	7 farms above mean
X2 (Mean: 4811.52)	17 farms above mean	5 farms above mean
X3 (Mean: 3815.69)	13 farms above mean	7 farms above mean
X4 (Mean: 9520.44)	15 farms above the mean	4 farms above mean

X5 (Mean: 5216.31)	10 farms above the mean	6 farms above mean
X6 (Mean: 8686.06)	7 farms above mean	7 farms above mean
Z Variables		
Z1 (Mean: 0.121; Std Dev: 0.326)	3 farms above mean	0 farms above mean
Z2 (Mean: 0.822; Std Dev: 0.383)	18 farms above mean	9 farms above mean
Z3 (Mean: 0.135; Std Dev: 0.341)	3 farms above mean	3 farms above mean
Z4 (Mean: 1.043; Std Dev: 1.328)	4 farms above mean	2 farms above mean
Z5 (Mean: 7.528; Std Dev: 3.584)	12 farms above mean	12 farms above mean
Z6 (Mean: 0.955; Std Dev: 0.207)	17 farms above mean	17 farms above mean
Agro-climatic Zones		
Zone 1	2 farms	11 farms
Zone 2	1 farm	3 farms
Zone 3	2 farms	0 farms
Zone 4	1 farm	2 farms
Zone 5	3 farms	2 farms
Zone 6	11 farms	2 farms

Source: Data has been self-generated in STATA using the PSLM dataset from 2014

Category	**Top Performing 20 Farms (2016)**	**Bottom Performing 20 Farms (2016)**
Cropping Patterns		
Wheat-Cotton	3 farms	0 farms
Wheat-Rice	0 farms	1 farm
Wheat-Sugarcane	4 farms	0 farms

Wheat-other	5 farms	11 farms
Crop number	1-6	1-5
X Variables		
X1 (Mean: 16.875)	2 farms above mean	7 farms above mean
X2 (Mean: 25410.66)	6 farms above mean	7 farms above mean
X3 (Mean: 12155.48)	4 farms above mean	10 farms above the mean
X4 (Mean: 21448.81)	7 farms above mean	4 farms above mean
X5 (Mean: 12469.78)	9 farms above mean	11farms above mean
X6 (Mean: 62003.57)	2 farms above mean	8 farms above the mean
Z Variables		
Z1 (Mean: 0.25; Std Dev: 0.4442617)	5 farms above mean	1 farm above mean
Z2 (Mean: 0.9; Std Dev: 0.3077935)	18 farms above mean	6 farms above mean
Z3 (Mean: 0.1; Std Dev: 0.3077935)	2 farms above mean	6 farms above mean
Z4 (Mean: 0.85; Std Dev: 1.663066)	8 farms above the mean	7 farms above mean
Z5 (Mean: 8.1; Std Dev: 2.989455)	8 farms above the mean	7 farms above mean
Z6 (Mean: 0.85; Std Dev: 0.3663475)	17 farms above mean	16 farms above mean
Agro-climatic Zones		
Zone 1	5 farms	6 farms
Zone 2	2 farms	8 farms
Zone 3	0 farms	2 farms
Zone 4	0 farm	2 farms
Zone 5	2 farms	1farms
Zone 6	2 farms	1 farm
Zone 7	2 farms	0 farms

Zone 8	1 farm	0 farms
Zone 9	6 farms	0 farms

Source: Data has been self-generated in STATA using the PSLM dataset from 2016

Category	**Top Performing 20 Farms (2019)**	**Bottom Performing 20 Farms (2019)**
Cropping Patterns		
Wheat-Cotton	1 farm	0 farms
Wheat-Rice	8 farms	0 farms
Wheat-Sugarcane	1 farm	0 farms
Wheat-other	8 farms	4 farms
Crop number	1-7	0-2
X Variables		
X1 (Mean: 7.352)	3 farms above the mean	5 farms above the mean
X2 (Mean: 21647.42)	6 farms above the mean	9 farms above the mean
X3 (Mean: 8773.591)	3 farms above the mean	5 farms above the mean
X4 (Mean: 34221.94)	6 farms above the mean	8 farms above the mean
X5 (Mean: 9860.706)	13 farms above the mean	8 farms above the mean
X6 (Mean: 19067.78)	4 farms above the mean	5 farms above the mean
Z Variables		
Z1 (Mean: 0.1; Std Dev: 0.3077935)	2 farms above the mean	0 farms above the mean
Z2 (Mean: 0.9; Std Dev: 0.3077935)	18 farms above the mean	7 farms above the mean
Z3 (Mean: 0.05; Std Dev: 0.2236068)	1 farm above the mean	4 farms above the mean
Z4 (Mean: 0.95; Std Dev: 1.316894)	9 farms above the mean	3 farms above the mean
Z5 (Mean: 11.35; Std Dev: 11.77095)	5 farms above the mean	9 farms above the mean

Z6 (Mean: 0.95; Std Dev: 0.2236068)	19 farms above the mean	16 farms above the mean
Agro-climatic Zones		
Zone 1	4 farms	14 farms
Zone 2	1 farm	0 farms
Zone 4	0 farms	1 farm
Zone 5	9 farms	1 farm
Zone 6	1 farm	1 farm
Zone 9	5 farms	3 farms

Source: Data has been self-generated in STATA using the PSLM dataset from 2019

References

Agyekum, K., Atakora, A., Kwasi Darfor, & Singh, S. (2015). Agricultural credit rationing by banks in Ghana: A case of smallholder farmers in the Upper West Region of Ghana. *Agricultural Finance Review, 75*(2), 174–191.

Benjamin, N., Mbaye, A. A., & Diop, S. (2014). *The informal sector in Francophone Africa: Firm size, productivity, and institutions* (World Bank Policy Research Working Paper No. 6888). Washington, DC: World Bank.

Iqbal, N., & Munir, S. (2018). An estimation of technical efficiency of strawberry production in District Charsadda, Khyber Pakhtunkhwa. *Journal of Agricultural Research, 56*(1), 69–78. https://doi.org/10. Accessed August 26, 2024.

International Labour Organization. (2023, August 1). How decent work can transform cotton production. *ILO News*. https://www.ilo.org/resource/news/how-decent-work-can-transform-cotton-production

International Labour Organization. (n.d.). Informal economy in Pakistan. *ILO Asia-Pacific*. https://www.ilo.org/regions-and-countries/asia-and-pacific-deprecated/areas-work/informal-economy-pakistan#:~:text=The%20 Accessed August 26, 2024.

Kasnakoğlu, H., & Yurdakul, M. (2016). The effect of the informal economy on income inequality: Evidence from Turkey. *Journal of Economics, Finance and Accounting, 3*(2), 135–146.

Simmons, T. J. (1999, February 2). An analysis of the technical efficiency of cotton farmers in the Punjab Province in Pakistan. *1999 Conference (43rd), January 20-22, 1999, Christchurch, New Zealand*. Australian Agricultural and Resource Economics Society. https://ideas.repec.org/p/ags/aare99/123815.html