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How did Supply and Demand Shocks Affect Industries and Occupations in COVID-19? Evidence from Pakistan

Muhammad Zubair Mumtaz
University of Bahrain, College of Business Administration, Sakhir, Bahrain.
National of University of Sciences & Technology, School of Social Sciences & Humanities, Islamabad, Pakistan
Email: zubairmumtaz76@gmail.com (Corresponding Author)

Zachary A. Smith
Saint Leo University, Tapia College of Business, FL, USA.
Email: zacharyasmith@gmail.com

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Abstract: This study examines the supply and demand shocks in Pakistan that affected occupations and industries during the COVID-19 pandemic. We use the remote labor index and essential scores for undertaking work activities from home across occupations proposed by del Rio-Chanona et al. (2020). To estimate demand shocks, we follow del Rio-Chanona et al. (2020), who employed estimates from the US Congressional Budget Office (2006) that attempted to forecast how the US economy would be affected at the industry level if a severe influenza epidemic occurred. We document that demand shocks most significantly affect the transport and food services industries. In contrast, the manufacturing, mining and quarrying, and handicraft and printing industries are likely to be impacted by supply shocks. Food services and restaurants experience a bigger combined shock. Relative to the pre-pandemic period, aggregate shocks suggest a decrease in the output of Pakistan's economy by one-fifth if the pandemic were to seriously affect the economy, threatening 21 percent of jobs and lowering total wage income by 18 percent. Considering a second wave and a new variant of coronavirus, we estimate that aggregate shocks may continue, and the economy's output could deteriorate by one-fourth if the region experiences a significant outbreak. Finally, we compare our findings with the US economy and find differences between supply and demand shocks in both economies.

Keywords: Shocks, COVID-19, Employment, Wages, Value-added.

JEL Classification: I15, J21, J23, J63, O49.

How did Supply and Demand Shocks Affect Industries and Occupations in COVID-19? Evidence from Pakistan

1. Introduction

The novel coronavirus (COVID-19) has had a severe impact on markets worldwide. To slow down the spread of the outbreak, governments restricted business activities, especially for "non-essential" businesses, and in some cases caused them to shut down. The demand in a handful of sectors (e.g., healthcare services) has increased; however, other sectors (e.g., air transportation and tourism) found that demand had declined (del Rio-Chanona et al., 2020). Moreover, several industries faced problems on the supply side owing to the imposition of restrictions on non-essential sectors.

Economists and analysts (Koren & Pető, 2020; Hicks et al., 2020) have begun to examine the economic impact of COVID-19 across many nations. Inoue & Todo (2020) analyze the effect of the closure of firms in Tokyo that would result in a loss of productivity in other segments of the economy, using a supply chain mechanism and report that after a month, daily productivity would be 86 percent lower than the pre-COVID period. Barrot et al. (2020) investigate industry-level shocks by indicating which industries are essential and which activities or occupations could be completed from home, and then simulate supply and demand shocks across these industries. They reported that six weeks of social distancing would result in an estimated decrease of 5.6 percent in GDP. In the Pakistani market, the World Bank predicts that economic activities would shrink by 1.0 percent in 2020 but rebound to a positive growth rate of 5.6 percent in 2021 (World Bank, 2022). This decrease in output may have reduced the demand for small industrial, manufacturing, and allied businesses.

This study examines the first-order supply and demand shocks for the Pakistani economy across industries and occupations resulting from the outbreak associated with COVID-19 or a similar pandemic-type event. All else equal, disruptions related to demand and supply-side shocks were likely to impact developing countries significantly. This study measures the effect of supply-side and demand-side variations in light of a pandemic (e.g., a surge in demand for healthcare services and a reduction in demand for goods and services). To estimate the supply and demand shocks, we follow the methodology of del Rio-Chanona et al. (2020). Supply shocks refer to a share of work that will not be performed (i.e., not from an essential industry -as defined in the context of the pandemic - and cannot be performed from home) because of the pandemic. Regarding demand shocks, we project the industry-level demand shocks onto all occupations listed within that industry.

This study extracts data from the Labor Force Survey 2017/18 for 355 occupations. Occupation-wise data is obtained from the Pakistan Standard Classification of Occupations (PSCO) (2015). The remote labor index (RLI) is used as a proxy to estimate the work activities that can be performed from home. RLI = 1 is classified as work activities that can be performed from home, and RLI = 0 reflects work activities that cannot be completed from home. Regarding RLI and the essential occupation score, we gather data from del Rio-Chanona et al. (2020), allocating a score to each 4-digit occupation in every 2-digit PSCO classification.

Occupations such as business and financial operations, information and communications, software and applications development, and office and administrative support have the highest RLI. In contrast, protective services, mining and construction, and building and related trades tend to have lower RLI. We estimate industry-specific RLI to investigate the supply shock in terms of specific industries. Industry-specific RLI is obtained by multiplying occupational RLI and the share of employment in a particular industry at the occupation level. Finance and insurance, information, professional, scientific and technical services, and management of companies and enterprises have the highest median RLI, while handicraft and printing, information and communications, and mining and quarrying have the lowest median RLI.

This study further investigates the vulnerability of employment based on supply shocks. The occupations with lower RLI scores were hand packers, cleaning and housekeeping supervisors, machine operators, and protective services. Occupations with higher RLI scores include finance and investment advisers, database designers and administrators, higher education teachers, management and organization analysts, and translators. This study also evaluates the combined effect of an essential industry and industry-specific RLI. We find that finance and investment, legal, information, software and applications, and business and finance operations get higher RLI scores and are classified as essential industries. Alternatively, mining and quarrying, agricultural, forestry and fishery, food services, and building and related trades have lower RLI and essential scores.

Aggregate shocks show a decrease in output by one-fifth in Pakistan's economy, one-fourth of current employment, and 18 percent of total wage income. The magnitude of these shocks differs considerably across various industries. Moreover, it is imperative to examine the effects of supply and demand shocks on the economy at the industry and occupational level to determine what segment of the working population will suffer the most due to a potential pandemic outbreak. In summary, we report that aggregate effects cause supply shocks that significantly influence the manufacturing and services sectors because they are categorized as non-essential, and the labor force associated with these industries cannot work from home. We also account for a second pandemic wave and estimate a decrease in value added by one-fourth, using scenario analysis. Similarly, supply and demand shocks also contribute to a reduction in industrial and production activities. Lastly, we compare our results with the US economy and observe the differences between supply and demand shocks between the two countries.

This study is organized as follows: Section 2 reviews the pandemic shocks. Section 3 describes the methodology and data to estimate the supply and demand shocks. In Section 4, we discuss the results, and Section 5 is the conclusion.

2. A review of pandemic shocks

Researchers have used several different tools and perspectives to estimate the potential economic and social impacts of a pandemic. These methods typically rely on deaths and collected mortality statistics to estimate the likely impact of the pandemic, or focus more on the disruption and impacts that measures such as social distancing policies and, school closures can have as a consequence. In this study, we focus more on the latter to ascertain the impact of a pandemic and the ensuing supply and demand shocks that affect the Pakistani economy.

As a starting point, Keogh-Brown et al. (2009) used four different modeling scenarios when projecting the effect of a pandemic on GDP: the impact of the disease, the effect of the disease and school closures, the impact of prophylactic absenteeism (healthy people leaving the workforce because of the threat potentially posed by the disease), and the combined impact of the disease, school closures, and prophylactic absenteeism. They also differentiated their estimates between milder, single-wave pandemics, which would likely cause a 9.5 percent and 2.5 percent reduction in GDP using a quarter and year time frame, respectively, and more severe pandemics, in which greater than 1 percent of the population dies, led to increased estimates of a -29.5 percent and -6.0 percent shock to GDP, respectively.

In a similar study, Keogh-Brown et al. (2010) modeled the potential impact of a pandemic flu outbreak on the economies of the UK, France, Belgium, and The Netherlands, using different rates of workdays lost due to illness, school closures in weeks, and prophylactic absenteeism in weeks. The mildest estimates from the pandemic were less than a 1 percent decline in GDP across all the countries in the study, and the largest estimate ranged from a 6 percent to 7.5 percent decrease in GDP. Interestingly, they also attempted to model the industry-level impact of mild and severe outbreaks and illustrate how each sector was likely to be impacted in mild and severe pandemics, which relates to our current paper: Agricultural, Retail, Hotels and Restaurants, Freight and Public Transport, Tourism and Travel, Post and Telecommunications, Insurance, Education, and Health and Social Work. In general, Keogh-Brown et al. observed minimal impact on Agriculture production (i.e., ~1 to 4 percent), moderate impact on Agricultural, Retail, Hotels and Restaurants, Freight and Public Transport, Tourism and travel, Post and Telecommunications, and Insurance (i.e., 2 percent to 6 percent), and a more severe impact on Education, and Health and Social Work (i.e., 3 percent to 10 percent), as they modeled mild to the severe effects stemming from a pandemic outbreak. In future sections, we will relate the losses due to absenteeism and school closures to more general disruptions in our ability to complete the tasks associated with occupations, owing to stricter social distancing and lockdown policies.

Grgurić & Jelić (2021) estimated Croatia's supply and demand shocks using potential output in the COVID-19 pandemic. To overcome these shocks, the Government of Croatia implemented expectational supply-side restrictions. They proposed an unconventional method to predict the output gap and estimated the potential GDP and capacity utilization rate. They reported that their scaled measure of potential GDP was consistent with other business cycle parameters. Luoa & Villar (2023) empirically examined the forecasts for cross-sectional price changes using input-output models with sticky prices. They undertook disaggregated industry-level data and identified that the response of prices to shocks is aligned with the estimated price change. However, they observed that differences in sectoral prices change over time in terms of the progression of the network structure. Their empirical analysis split demand and supply shocks, and found that aggregate demand shocks and production significantly increased inflation in the period 2021-2022. In another study, Serrano (2023) modeled a partial equilibrium framework for non-financial firms (operating in the European Union as suppliers, end-producers, and service providers) to boost production in the eve of demand and supply shocks. They found that demand shocks were more prevalent, and the prices were expected to fall during the phase of the pandemic, which resulted in an increased supply of intermediate goods and created supply shocks (Louchichi et al., 2021).

A number of studies have examined the efficacy of fiscal and monetary counterfactors regarding economic turndown due to natural catastrophes and financial crises (Keen & Pakko, 2007; Flessa & Marx, 2016; Guerrieri et al., 2020). For instance, Porsse et al. (2020) forecasted the economic effects and fiscal counter parameters during the COVID-19 pandemic. As per their findings, government fiscal measures partly reduced GDP losses from 3.78 percent to 0.48 percent and 10.90 percent to 7.64 percent in forecasting under various severity levels. According to them, researchers (Hallegatte, 2008; Sangsubhan & Basri, 2012) have utilized multiple techniques, but they overlooked this effect that may overemphasize the consideration of counter parameters in overcoming economic losses (Haldane, 2020; Bigio et al., 2020).

As our paper relates specifically to Asia and Pakistan, Abiad et al. (2020) estimated the potential impact of the COVID-19 pandemic across Asia and provided estimates across different regions throughout the world for both 2020 and 2021 with a low, baseline, and high estimate for the losses due to the pandemic. Specifically, in South Asia, their estimates were -10 percent, -13.2 percent, and -16.3 percent, respectively for 2020, and -7.0 percent, -9.4 percent, and -11.8 percent, respectively in 2021. In addition to supply and demand shocks, they indicate that precautionary behaviors, containment policies, declines in mobility, travel bans, border closures, and a general reluctance to travel indirectly impact trade and production. These estimates could provide a comparison to our general results. Mumtaz (2021) analyzed the behavior of 19 stock markets on the eve of the coronavirus pandemic using neuro-fuzzy systems. He used the daily data between the date of the first reported case in the country and August 31, 2020, and found that stock indices were highly volatile and generally produced negative average returns except in a few markets. Moreover, he reported that the neuro-fuzzy system estimates the pattern of stock indices with an average accuracy of 66 percent.

From Keogh-Brown et al. (2009), Keogh-Brown et al. (2010), and Abiad et al. (2020), we see that the effect of a pandemic on a particular economy can be modeled using measures associated with whether we can do our jobs when a pandemic occurs and the impact that the pandemic has on our ability to complete our work. Similarly, Brinca, Duarte, & Castro (2021) illustrate that pandemics, like the COVID-19 outbreak, will cause demand and supply shocks and distinguish between the two types of shocks. A supply shock is an effect that would restrict the economy from producing output at prevailing prices. A demand shock would occur due to the willingness or ability of consumers to purchase goods and services. If workers lose their jobs, they are not, in general, able to purchase the same level of goods and services that they were able to purchase when employed; additionally, restrictions that are imposed upon them by government agencies prohibit them from engaging in certain activities (e.g., eating out in restaurants, getting their hair cut, etc.) cause additional stress to the economic system. In this study, we intend to simplify the variables we use as proxies to estimate a pandemic's likely impact on a particular region using the methodology created by del Rio-Chanona et al. (2020), highlighted in the following sections. In the following few sections, we will illustrate how we estimate the potential demand and supply shocks that could influence Pakistan's output in light of the COVID-19 pandemic.

3. Methodology and data

3.1 Estimating supply shocks

We follow the del Rio-Chanona et al. (2020) proxy for supply-side shocks, which does not take into consideration the loss of workers due to illness or death but considers (a) whether each occupation is considered '*essential*' and (b) whether each occupational task can be completed '*remotely*.'

To answer the question about the "essential" nature of a particular occupation, del Rio-Chanona et al. (2020) relied on a list of Italian "Essential Industries" as Italy was one of the first countries to be affected by the pandemic; its availability, and its assumed applicability to other regions. Though there are likely to be some regional disparities in the classification of essential industries, most critical occupations are likely to be applicable across regions. They used the NACE (Statistical Classification of Economic Activities in the European Community) and associated them with NAICS codes, thus mapping the essential scores from NACE to NAICS. After obtaining a mapping from the NACE to the NAICS, the three authors and two additional colleagues proceeded to edit their mapping to ensure accuracy.

3.1.1 Industry-specific shocks

In the first step, we map 4-digit PSCO with NAICS to obtain the proportion of work carried out from home that can also be referred to as "occupation-level RLI." In the next step, we measure the industry-specific RLI. We employ a weighted average of the occupation-level RLI for each industry i, referring to the proportion of workers engaged in each occupation and industry. As work activities are associated with occupations only, we apply the weighted averages to get the industry-specific RLI. Suppose, $\tilde{X}$ is the row-normalized form of matrix X, i.e., $\tilde{X}_{ji} = X_{ji}/\sum_h X_{jh}$. Likewise, we assume that the element of matrix $\widetilde{N}$ be $\widetilde{N}_{mj} = N_{mj}/\sum_h N_{mh}$. We express industry-specific RLI as:

$$r = \widetilde{N}\tilde{X}v \tag{1}$$

Equation 1 represents the RLI of an industry, and r_m shows the proportion of work in an industry m that can be undertaken from home. In evaluating industry-related shocks, measuring the magnitude of industries exposed is crucial. Industry-specific shocks (ISS) are computed as:

$$ISS_m = -(1 - e_m)(1 - r_m) \tag{2}$$

where e_m represents essential score, r_m refers to RLI showing the proportion of work that can be undertaken from home. The correlation between e_m and r_m is 0.40, which is statistically significant (p-value = 0.015). This evidence suggests that industry RLI and essential score are dependent on each other.

3.1.2 Occupation-specific shocks

To determine whether a particular occupation could be done remotely or the RLI (Remote Labor Index), del Rio-Chanona et al. (2020) used the O*NET work activities related to specific occupations, most which have at least five work activities that fall under a particular occupation. They then classified them as being able to be completed from home or not (i.e., RLI of 1 and RLI of 0, respectively). To classify a particular occupation as an RLI of 1, all activities associated with that specific occupation would have to have an RLI of 1. Likewise, all work activities were given the same weight, which is a simplifying assumption, and they assume that if one work activity could not be done remotely, the others would not be affected. What resulted was a weighted average of work activity scores that generated an occupational-level RLI. Like equation 2, occupation-specific shocks (OSS) can be obtained.

$$OSS_j = -(1 - x_j)(1 - y_j) \tag{3}$$

where x_j shows the essential score and y_j refers to RLI, indicating the occupation-specific work that can be performed from home. The correlation between occupation-specific RLI and the essential score is 0.32, and their relationship is statistically significant ($p - value \leq 0.001$). This evidence illustrates that occupation-specific RLI and essential scores depend on each other. We conclude that both occupation- and industry-specific RLI are based on their essential scores.

3.2 *Estimating demand shocks*

We use the severe shocks identified by the Congressional Budget Office (2006) that Rio-Chanona et al. (2020) employed to determine the demand shock. The demand shocks are estimated on the 2-digit PSCO level based on the specific industry classification. Further, it is presumed that demand shocks similarly affect all sub-industries. Suppose the share of industry demand shock for industry $m = -IDS_m$. In line with supply shocks, we scale the demand shocks onto occupations. The occupation-related shock from the demand side of the economy is estimated as follows:

$$ODS = N^{*T} IDS \tag{4}$$

3.3 *Estimating Aggregate Shocks*

We aggregate supply and demand shocks to find how the estimates influence employment, total wage income, and the output of the economy. We also compute employment total shocks (OSS x employment in an occupation + ODS x employment in an industry). Likewise, we find total wages and value-added shocks that contribute to aggregate shocks.[1]

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[1] We merge both supply and demand shocks to total instant shocks for occupations and industries. The shocks are negative as they may reduce the output. Mathematically, industry total shock is shown as $ITS_m = min(ISS_m, IDS_m)$ and the occupational total shock is $OTS_j = min(OSS_j, ODS_j)$.
To examine the shocks, we use aggregate industry or occupation-specific shocks. We determine them by allocating the weights. Applying the vector L to signify the proportion of employed workers that are employed by occupation j, we get: $Employmenttotalshocks = OTS^T L$. The employment demand shock is estimated by using ODS. In this study, we assume how much paid wages will fall. For each occupation, we measure the total wage bill by multiplying the number of workers by the average wage. As a result, we obtain: $Wagetotalshock = OTS^T w$. where w denote a vector and w_j

3.4 Data

The data relating to industries and employment is obtained from the Labor Force Survey, 2017/18. We use the occupation-specific RLI and essential score developed by del Rio-Chanona et al. (2020). We take the proportion of citizens employed in each occupation and aggregate those occupations to generate an industry-level score between 0 and 100 percent, indicating how much of the industry's employment can be carried out from home. We estimate our results based on the first wave of the pandemic. To estimate the demand shocks, we follow del Rio-Chanona et al. (2020), where they used estimates from the US Congressional Budget Office (2006).

4. Results

4.1 Supply shocks

Supply shocks are estimated by computing the share of work that did not fall under an essential industry and cannot be undertaken from home.

4.1.1 Work to be carried out from home

Earlier studies analyzed the magnitude of work that can be undertaken during COVID-19. Surveying China during the lockdown in late February, Zhang et al. (2020) document that 38 percent of the labor force worked from home, 27 percent sustained working through the office, and 25 percent stopped working. In another study, Adams-Prassl et al. (2020) conducted surveys in the UK and the US in late March of 2020, arguing that the proportion of work that could be undertaken from home differs extensively between occupations. Additionally, they document that higher-wage occupations were more inclined to work from home. Rio-Chanona et al. (2020) examine the US economy's supply shocks using occupation-specific and industry-specific RLI. They report that the fraction of work that can be undertaken from home varies across occupations and industries. Hicks, Faulk, & Devaraj (2020) evaluate the extent to which an occupation required "work with others" or "physical proximity to others"

is the proportion of occupation j in total wage bill. We do it for OSS and ODS. Lastly, to obtain an estimate of loss of GDP, we can aggregate shocks by industry, weighting by the proportion of an industry in GDP. We represent Y the vector and Y_m is the value-added of industry n divided by GDP, and estimate $Valueaddedtotalshock = ITS^T Y$. Likewise, we estimate the industry supply and demand shocks (ISS and IDS).

and determine that social distancing played an important role in influencing occupations during the pandemic.

4.1.2 Work activities to occupations

To obtain the occupation-specific data, we map PSCO with O*NET occupational codes, and our final sample consists of 355 occupations. Relating to RLI and essential occupation score, we obtain data from Rio-Chanona et al. (2020) after scaling the occupation-specific variable. Table 1 summarizes the top and bottom ten occupations segregated based on the share of work activities undertaken from home.

Table 1: Ranking of occupations based on remote labor index

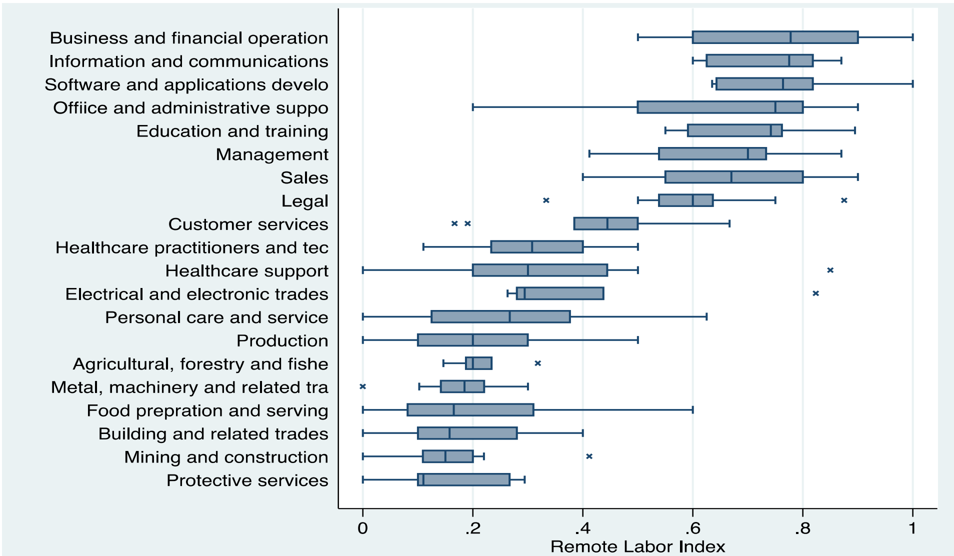
Occupations	RLI
Financial and investment advisers	1.00
Database designers and administrators	1.00
Government social benefits officials	0.92
Research and development managers	0.90
University and high education teachers	0.89
Management and organization analysts	0.89
Translators, interpreters, and other linguists	0.88
Government licensing officials	0.87
Retail and wholesale trade managers	0.86
Nursing associate professionals	0.85
….	
Poultry producers	0.00
Musical instrument makers and tuners	0.00
Packing, bottling, and labelling machine operators	0.00
Paper products and machine operators	0.00
Cement, stone, and other mineral products machine operators	0.00
Protective services workers not elsewhere classified	0.00
Cleaning and housekeeping supervisors in offices, hotels and other establishments	0.00
Drivers of animal-drawn vehicles and machinery	0.00
Hand packers	0.00
Aquaculture and fisheries production managers	0.00

This table presents the top and bottom ten occupations classified based on the fraction of work activities undertaken from home. Data sources include Labor Force Survey (2017/18) and del Rio-Chanona et al. (2020).

To examine the level of RLI across occupations, Figure 1 exhibits the boxplots showing the allocation of RLI for each 4-digit occupation in every 2-digit PSCO classification. Occupations associated with business and financial operations, information and communications, software and applications development, and office and administrative support tend to have the highest

RLI. In contrast, occupations with the lowest RLI include protective services, mining and construction, and building and related trades.

Figure 1: Segregation of remote labor index across occupations

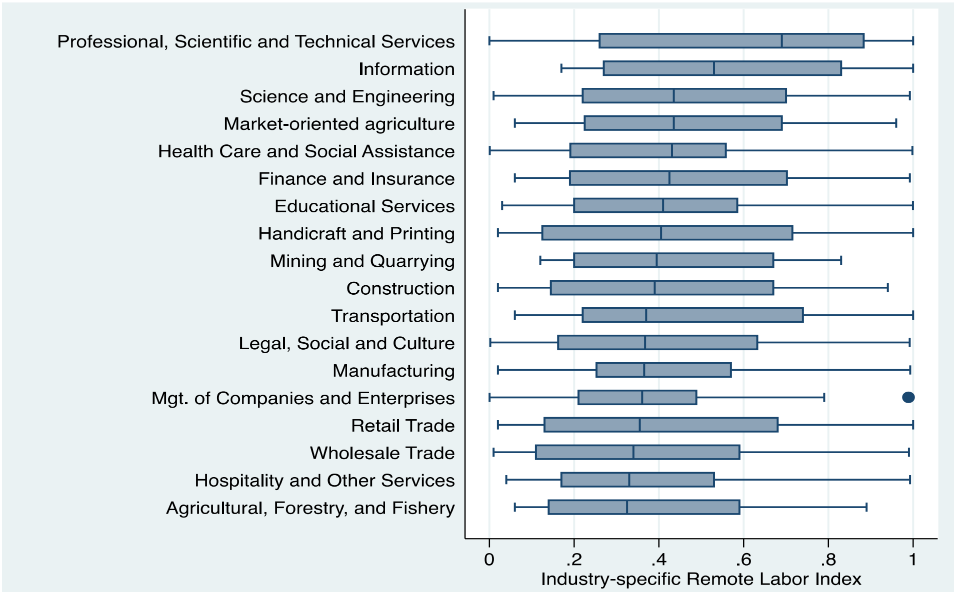


The diagram exhibits the allocation of RLI for each 4-digit occupation in each 2-digit PSCO classification. Data sources include Labor Force Survey (2017/18) and del Rio-Chanona et al. (2020).

4.1.3 Work activities from occupations to industries

This section estimates industry-specific RLI to measure supply shocks relating to specific industries caused by social distancing. We obtain industry-specific RLI by multiplying occupational RLI with a proportion of employment in a particular industry. Initially, we map 4-digit occupations within the 2-digit PSCO industry classification. Figure 2 shows the 2-digit PSCO industry classifications based on the median values of every underlying allocation. Considering the large dispersion in different occupations within a broad range of industry categories, we find an extensive distribution. The results show the highest median RLI values of industries covering finance and investment, information technology, professional, scientific and technical services, and management of companies and enterprises. Alternatively, industries like hospitality and other services, agriculture, forestry, and fisheries, handicraft and printing, and mining and quarrying tend to have the lowest median RLI.

Figure 2: Allocation of remote labor index across industries



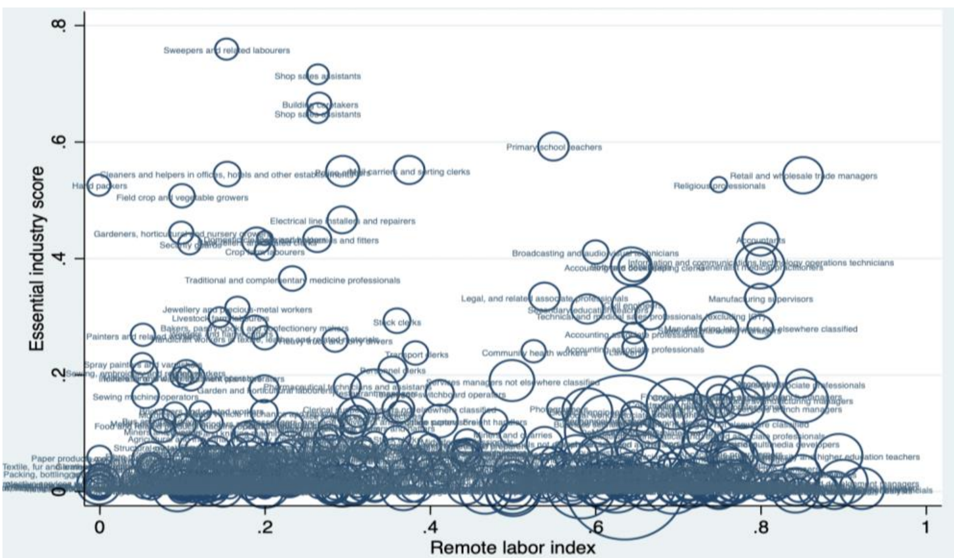
The diagram exhibits the allocation of RLI for each 4-digit occupation in each 2-digit PSCO industry classification. Data sources include Labor Force Survey (2017/18) and del Rio-Chanona et al. (2020).

4.1.4 Non-essential and essential industries

This section examines the mixed effect on the labor supply in Pakistan by assessing what proportion of employment is essential in a particular industry and the probability that workers in a certain occupation can perform work activities from home. Figure 3 presents the susceptibility of occupations based on supply-side shocks. Every circle in the diagram indicates an occupation, the share of current employment, and the median wage in every occupation, showing the size of the circle. The lower occupation RLI includes hand packers, cleaning and housekeeping supervisors, machine operators, and protective services, reflecting the lower probability of performing the required activities even in an essential industry. Considering the effect of social distancing that causes supply-side shocks, it is more likely that workers in these occupations would lose their jobs or possibly have their work hours reduced. Occupations with higher RLI scores cover finance and investment advisers, database designers and administrators, higher education teachers, management and organization analysts, and translators. The susceptibility of these occupations toward supply-side shocks would be lower. The graph further illustrates that occupations like healthcare professionals, livestock workers, and physiotherapists have a lower probability of undertaking their work activities at home; however, a higher probability exists for these occupations to be employed in an essential industry and cause lower economic vulnerability to supply-side shocks. Additionally, some occupations are classified as non-essential industries and have a lower propensity to work from home.

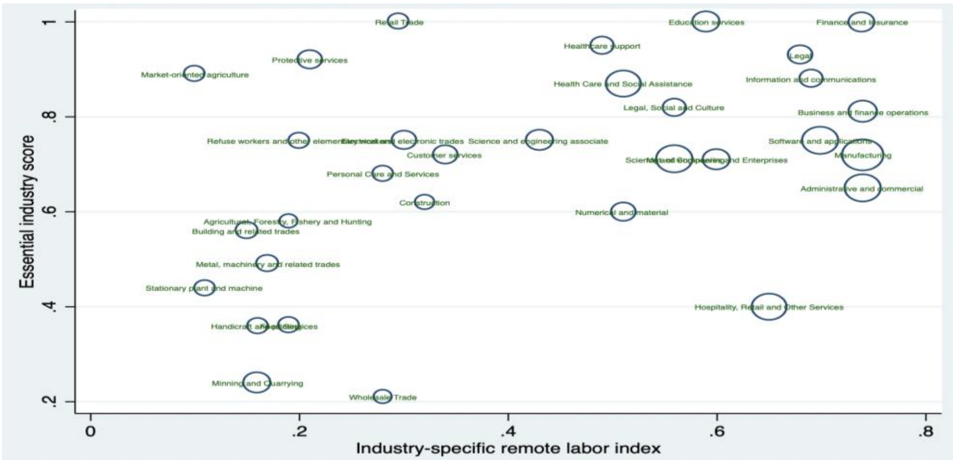
We investigate the combined effect of an essential industry and industry-specific RLI to measure supply-side shocks on the same pattern. Industries (e.g., finance and investment, legal, information technology, software and applications, and business and finance operations) tend to have higher RLI scores and are likely to be categorized as essential industries. This implies that the vulnerability of these industries towards demand-side shocks would be lower. In contrast, industries such as mining and quarrying, agriculture, forestry, fishery and hunting, food services, and building and related trades have lower RLI scores and are less likely to segregate them as a part of essential industries. These industries have higher probabilities of inflating supply-side shocks.

Figure 3: A comparison between the proportion of employment in an essential industry and occupational RLI



This graph exhibits the relationship between essential industries, occupational RLI, and median wages. In the presence of social distancing, a high RLI and a higher proportion of workers associated with essential industries are less susceptible to loss of employment and vice versa. Data sources include Labor Force Survey (2017/18) and del Rio-Chanona et al. (2020).

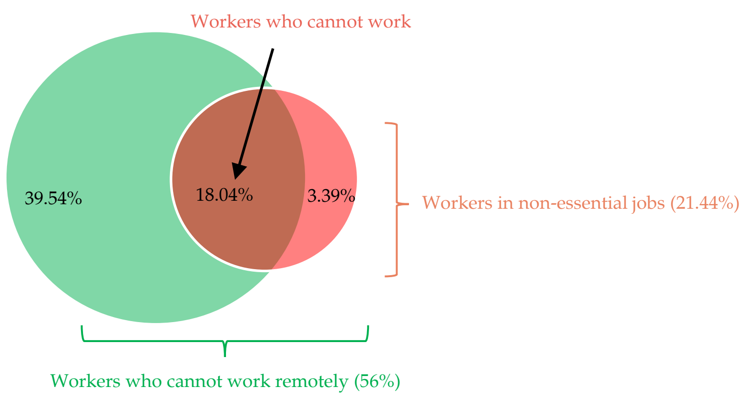
Figure 4: A comparison between the proportion of employment in an essential industry and industry-specific RLI



This graph exhibits the relationship between essential industries, industry-specific RLI, and median wages. Data sources include Labor Force Survey (2017/18) and del Rio-Chanona et al. (2020).

Figure 5 summarizes the key findings to understand how many workers could not work from home. A Venn diagram illustrates that 21.44 percent of workers are associated with non-essential jobs, 56 percent cannot perform their jobs remotely, and 18.04 percent are related to non-essential jobs that cannot be done remotely. This further implies that 39.01 percent of workers can work remotely and are essential workers.

Figure 5: Workers that cannot work



This figure illustrates that 21.44 percent of workers are classified in a non-essential job, 56 percent cannot work remotely, and 18.04 percent are linked with non-essential jobs and do not work remotely. The remaining workers (39.01 percent) relate to essential jobs that can be done remotely. Data sources include Labor Force Survey (2017/18) and del Rio-Chanona et al. (2020).

4.2 *Demand shocks*

Recent studies [see Rio-Chanona et al. (2020) and Baker et al. (2020)] document that COVID-19 has adversely affected consumer spending behavior. The demand for health services has increased in response to the virus. Alternatively, the demand for products and services has also influenced the presence of this pandemic. In the event of COVID-19, Baker et al. (2020) report the spillover effect, which can be observed with an increase in the retail sector's direct demand.

There are no official sources for ascertaining demand shocks in Pakistan – as a result, we are utilizing US Congressional Budget Office (2006) estimates developed to capture influenza pandemic shocks following del Rio-Chanona et al. (2006). We use these estimates to find approximate demand shocks in the country. Table 2 shows the severity of demand shock based on industry category.

Table 2: Categorization of the sector-wise demand shock

Broad industry category	**Severe scenario shock**
Agriculture	–10
Mining	–10
Utilities	0
Construction	–10
Manufacturing	–10
Retail trade	–10
Transportation and warehousing	–10
Information	–67
Finance	0
Professional and business activities	0
Education	0
Healthcare	15
Arts and recreation	–80
Accommodation/ food service	–80
Other services except government	–5
Government	0

This table presents demand shock estimated by the US Congressional Budget Office (2006). [Source: del Rio-Chanona et al. (2020), p S108]

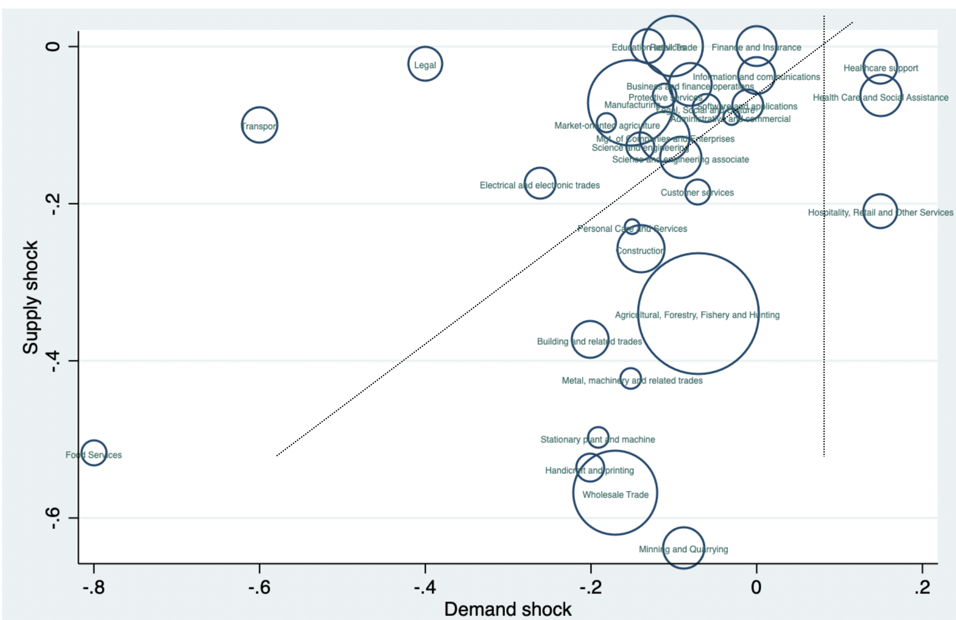
4.3 *A combined effect of supply and demand shocks*

In this section, we contrast the findings of the supply and demand shocks at the industry and occupation levels.

4.3.1 Industry-specific supply and demand shocks

This study analyzes the combined effect of supply and demand shocks for every industry (Figure 6). The magnitude of the circles represents the share of the gross output of the industries. As essential industries are falling on the horizontal line, they face no supply shock. Among these industries, finance and insurance, information technology, and administrative and commercial have no demand shock as we assume that demand for their output remains the same. The diagram has displayed a surge in demand for all health-related sectors in the country. In contrast, the transport sector shows a decline in demand and falls above the fitted line. This implies that the demand for an essential industry such as transport has decreased owing to the impacts of the pandemic.

Figure 6: Supply and demand shocks for industries



This diagram exhibits the industry-specific supply and demand shocks. Each circle represents the share of gross output. Data sources include Labor Force Survey (2017/18) and del Rio-Chanona et al. (2020).

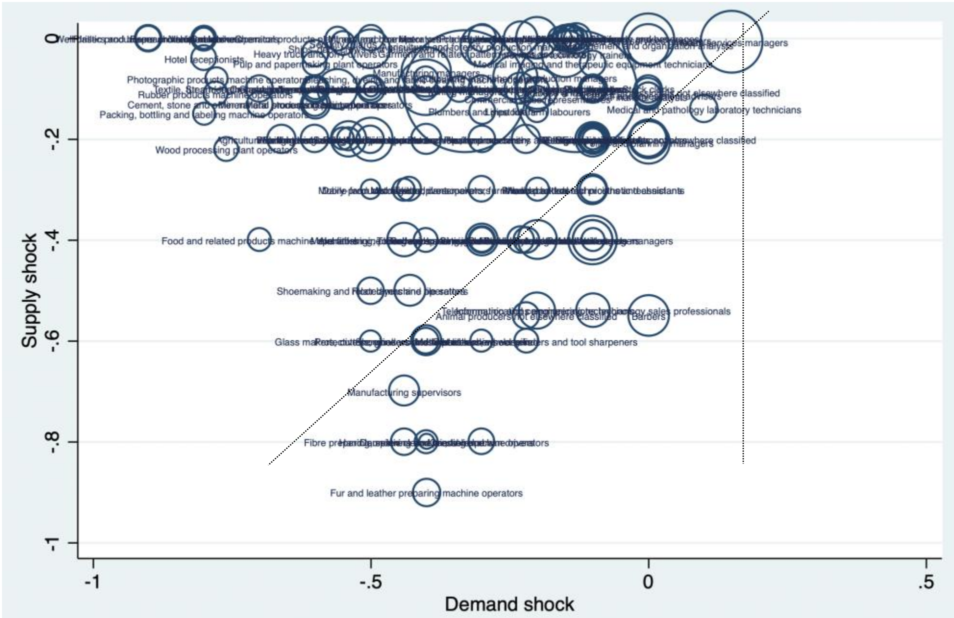
On the other hand, non-essential industries like food services also appear to indicate a downward trend in demand- and supply-side. This illustrates that the government restricted dine-in activities to prevent the coronavirus, which adversely affected Pakistan's restaurant businesses. By comparing the demand and supply shocks, we can argue that demand shock is more severe and falls above the fitted line. A few non-essential industries (e.g., wholesale trade, manufacturing, and mining and quarrying) faced higher supply shocks relative to demand shocks, thereby appearing below the fitted line.

4.3.2 Occupational-specific supply and demand shocks

We assume that occupations are affected owing to a lack of supply or demand in a particular industry. Figure 7 presents the occupational-specific supply and demand shocks. The surge in the pandemic led to increased health-related activities. It is evident from the diagram that the demand for healthcare services, medical equipment, and nurses rose substantially. Occupations such as heavy trucks and lorry drivers, hotel receptionists, and food products appeared to bear mild supply shocks but significant demand shocks as they fall above the fitted line. This implies a reduction in transportation and food services as a result of the government imposing a swift and "smart" lockdown.

Other occupations, for instance, fur and leather preparing machine operators; manufacturing supervisors; glassmakers, cutters, grinders, and finishers; and chemical products plant and machine operators, have higher supply shocks as these jobs cannot be performed from home. Lastly, machine operators have higher demand and supply shocks for food and related products. This shows that restaurant business demand decreased as it can be challenging to undertake work activities from home.

Figure 7: Supply and demand shocks for occupations



This diagram exhibits the occupational-specific supply and demand shocks. Each circle represents the median wage of the occupation. The correlation between demand shocks and median wage is 0.16 (p-value = 0.073), and between supply shocks and median wage is 0.26. (p-value = 0.262). Data sources include Labor Force Survey (2017/18) and del Rio-Chanona et al. (2020).

4.4 Aggregate shocks

We estimate the aggregate shocks to determine their effect on the entire economy. In a particular industry, the total shock is the mix of demand- and supply shocks, assuming 15 percent as a demand shock and 25 percent as a supply shock. This demonstrates that 25 percent of the workforce cannot undertake their work activities, effecting the particular shock to the output. In the supply-constrained industries, the output is reduced due to a decline in labor supply. We also illustrate that workers' demand shock equals the output demand shock in an industry. For instance, the transport sector experiences a 67 percent demand shock and no supply shock; however, drivers associated with this industry face a 67 percent employment shock. This shows that occupational shock is based on the dominance of occupation in an industry.

Table 3: Aggregate shocks to employment, wages, and value-added

Aggregate shock	Employment	Wages	Value added
Supply shock	–22	–15	–17
Demand shock	–14	–9	–7
Total shock	–25	–18	–21

This table computes the size of each aggregate shock in percentage. Data sources include Labor Force Survey (2017/18) and del Rio-Chanona et al. (2020).

We evaluate aggregate shocks based on employment, wages, and value-added. Table 3 exhibits the results of aggregate shocks. The findings indicate that the total shock in employment was 25 percent higher than the total shock in wages paid and value-added. This further suggests that the employment level has declined by 22 percent and 14 percent due to supply and demand shocks. We report that supply shock is more severe than demand shocks in all the scenarios. Similarly, the wage shock is 18 percent lower than employment and value-added shocks. The estimated total shock in output is 21 percent, which explains that the pandemic halted one-fifth of industrial and business activities.

4.5 Wage-level shocks

Table 4 summarizes the results of total wage loss or employment shocks in the economy by dividing the sample into quartiles. Q_1 refers to the lowest quartile in terms of salary structure. Labor shock is estimated at the occupational level, which shows the decline in employment in total shocks in industries related to every occupation. An observation of interest is that the highest employment shock is associated with the top quartile and higher wage loss. This finding does not corroborate with del Rio-Chanona et al. (2020), as they report that the highest quartile of wages has low employment shock.

Table 4: Total wages or employment shocks using wage quartile

	Q_1	Q_2	Q_3	Q_4	Aggregate
Percentage change in employment	–32	–16	–26	–33	–20
Share of total lost wages (%)	17	23	20	40	19

This table presents total wages and employment shocks. We split our sample into wage quartiles depending on their occupation's average wage. Q_1 shows the least-paid workers. A vulnerable workforce obtains employment vulnerability in each quartile scaled by the total exposure. The share of total wage loss in the economy is related to vulnerable workers in each quartile. Data sources include Labor Force Survey (2017/18) and del Rio-Chanona et al. (2020).

4.6 Demand and supply shocks in the second wave and a new variant of coronavirus

Regarding the second wave of the coronavirus, a new variant of the virus was detected in the middle of December 2020 and spread rapidly in England, raising concerns for other countries. The new variant accounted for more than 60 percent of the cases in London, where the government locked down most parts of the country. This state of the condition caused an increase in the hospitalization rate and closure of industrial activities. Most countries discontinued travel arrangements with the UK for approximately a week, as a result. News reports indicated that the new virus variant also reached other countries.

This alarming situation created adverse economic conditions worldwide. The supply and demand shocks went further, as we estimated in the case of Pakistan. Schools were closed from November 2020 (and have since opened, though they continue to be heavily reliant on Government of Pakistan health advisories), and a smart lockdown was imposed in most parts of the country to overcome the virus outbreak. We assume that the imposition of lockdown creates occupational and industry-level shocks. Most importantly, supply and demand shocks further deteriorated the country's output. The occupations that do not perform their work activities from home affect the industrial and business activities, eventually reducing production activities.

Table 5: Scenario-based projection of aggregate shocks to employment, wages, and value added

Aggregate shock	Estimated Shocks			10% increase			20% increase		
	Employment	Wages	Value added	Employment	Wages	Value added	Employment	Wages	Value added
Supply shock	–22	–15	–17	–24	–17	–19	–26	–18	–20
Demand shock	–14	–9	–7	–15	–10	–8	–17	–11	–8
Total shock	–25	–18	–21	–28	–20	–23	–30	–22	–25

This table computes the size of each aggregate shock in percentage. We assume that aggregate shocks increase by 10% and 20% in the presence of a second wave and a new coronavirus variant. Data sources include Labor Force Survey (2017/18) and del Rio-Chanona et al. (2020).

We had surmised that the virus would continue to influence Pakistan in 2021; the estimated supply and demand shocks would have increased by 10 percent and, in the worst case, may have been inflated by

20 percent. Table 5 shows the projected percentages of aggregate shocks to employment, wages, and value-added. In the case of a 10 percent increase in estimated shocks, the results report a surge in shocks in employment of 28 percent, wages by 20 percent, and value-added by 23 percent. The assumption that estimated shocks increase by 20 percent reduces the country's output by one-fourth.

4.7 Comparing supply and demand shocks with the US economy

This section compares the results of supply and demand shocks in Pakistan and the US economies. As such, the extent of shocks may vary in developed and emerging economies. Del Rio-Chanona et al. (2020) examined the supply and demand shocks during COVID-19 pandemic using the US's occupational and industrial data. Adams-Prassl et al. (2020) documented that the proportion of work that can be done from home varies extensively between occupations.

Del Rio-Chanona et al. (2020) measured RLI as a proxy to estimate the work activities that could be undertaken from home. They used 740 occupations and measured occupation-specific RLI. They report that education, training and library, computer and mathematical, and business financial roles tended to have the highest RLI, meaning these occupations had the highest propensity to perform work activities from home. In contrast, production farming, fishing, and forestry, and construction and extraction had lower RLI. This study finds that occupations with the highest RLI include business and financial operation, information and communications, software and applications development, and office and administrative support. Simultaneously, the lower RLI covers protective services, mining and construction, and building and related trades.

To examine how many workers cannot work from home, del Rio-Chanona et al. (2020) report that 33 percent of workers are associated with non-essential jobs, 19 percent of workers could not work from home, and 56 percent could not work remotely. Additionally, 30 percent of workers are in essential jobs where they can work remotely. This study documents slightly different results wherein 21.44 percent of workers are associated with non-essential jobs, 56 percent cannot perform their jobs remotely, and 18.04 percent were related to non-essential jobs that do not perform remotely.

We also compare industry-specific supply and demand shocks in the US and Pakistan. Del Rio-Chanona et al. (2020) report that transport sector demand has decreased, whereas entertainment, restaurants, and hotels experienced demand and supply shocks. A handful of non-essential industries, such as manufacturing, mining, and retail, faced higher supply shocks than demand shocks. This study reported a decline in demand for the transport sector. Del Rio-Chanona et al. (2020) found that occupations like stonemasons, rock splitters, roofers, and floor layers bore strong supply shocks as workers cannot carry out work activates from home, owing to the nature of their occupations. This study observed that occupations such as fur and leather preparing machine operators, manufacturing supervisors, glassmakers, cutters, grinders, and finishers, and chemical products plant and machine operators have higher supply shocks.

Finally, we differentiated between aggregate shocks in developed and emerging economies. Del Rio-Chanona et al. (2020) identified aggregate shocks from employment (23 percent), wages (16 percent), and value-added (20 percent). It is important to note that the aggregate shocks in Pakistan is higher from employment (25 percent), wages (18 percent), and value-added (21 percent). This evidence indicates that the small size of Pakistani economy's size led to aggregate shocks on the eve of the coronavirus pandemic being higher than that of the US.

5. Conclusion

This project estimated the first-order supply and demand shocks in Pakistan across industries and occupations in the light of the COVID pandemic. We measured the impact of a supply-side shock due to the closure of non-essential industries as workers cannot work from home and demand-side variations that reduced the demand for goods and services. This study follows the methodology of Rio-Chanona et al. (2020) to estimate supply and demand shocks. We gather data from the Labor Force Survey 2017/18 and PSCO. We use RLI and essential scores to assess the work activities performed from home by scaling 4-digit occupation in every 2-digit PSCO classification.

Regarding employment vulnerability towards supply shocks, this study documents that hand-packers, cleaning and housekeeping supervisors, machine operators, and protective services tend to obtain lower occupational RLI. In contrast, finance and investment advisers, database designers and administrators, higher education teachers, management and organization analysts, and translators tend to have higher occupation RLI. While examining the combined effect of an essential industry and industry-specific RLI, this study reports that finance and investment, legal, information technology, software and applications, and business and finance operations obtain higher RLI values and are segregated under essential industries. On the other hand, mining and quarrying, agricultural, forestry, fishery and hunting, food services, and building and related trades have lower RLI scores.

Overall, we report an aggregate decrease in output by one-fifth, current employment by one-fourth, and total wage income by 18 percent. The magnitude of these shocks varies across industries. In general, aggregate shocks are prevalent due to supply shocks wherein the manufacturing and services sectors were categorized as non-essential as the labor force associated with these industries could not work from home. Another finding of this study was that the highest total wage loss was associated with the highest employment shocks. Considering newer waves, and newer variants, of the coronavirus, we estimated a decrease in value-added by one-fourth in the worst scenario. This effect will inflate supply and demand shocks, contributing to the reduction of industrial activities. This study also contrasts the US economy's findings and reports that supply and demand shocks vary between economies.

This study is helpful for policymakers to account for necessary measures for overcoming the output shock, which is one-fifth of the value-added. Industries such as manufacturing may be operative considering the parameters of social distancing, which will help increase the output and reduce the extent of shock. The government must formulate strategies for returning employees to work from their offices in the future, such as testing for the virus.

Furthermore, the government must announce aggressive monetary and fiscal policies to minimize the first-order shock and restrict the second-order shock. This will bring workers back into employment to preserve business and financial solvency. It is also proposed that the Government formulate disaster plans that may reduce the severity of loss and what course of action it can take in case of any eventuality, particularly a possible global resurgence in coronavirus infections. The possible limitation of this study is to develop RLI by scaling the factors with the US market and making a comparison with the elements that prevailed in American markets. For future research, it is proposed to examine the supply and demand shocks in different emerging economies and compare diverse factors.

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