197

RESEARCH REPORT

Agglomeration and Resilience: Impact of COVID-19 on Clustered and Non-Clustered SMEs in Bangladesh

Kazi Iqbal
Tanveer Mahmood
Md Nahid Ferdous Pabon

Bangladesh Institute of Development Studies (BIDS)

RESEARCH REPORT

AGGLOMERATION AND RESILIENCE: IMPACT OF COVID-19 ON CLUSTERED AND NON-CLUSTERED SMES IN BANGLADESH

Kazi Iqbal
Tanveer Mahmood
Md Nahid Ferdous Pabon

November 2023

BANGLADESH INSTITUTE OF DEVELOPMENT STUDIES

Research Report No. 197

Kazi Iqbal
Research Director
Bangladesh Institute of Development Studies (BIDS)
Dhaka, Bangladesh

Tanveer Mahmood
Lecturer
University of Dhaka
Dhaka, Bangladesh

Md Nahid Ferdous Pabon
Research Fellow
Bangladesh Institute of Development Studies (BIDS)
Dhaka, Bangladesh

Published by

Bangladesh Institute of Development Studies
E-17, Agargaon, Sher-e-Bangla Nagar
G.P.O. Box No. 3854, Dhaka-1207, Bangladesh
Phone: 880-2-58160430-37
FAX: 880-2-58160410
Website: www.bids.org.bd
E-mail: publication@bids.org.bd

Price:	Inland	Foreign
	Tk. 100.00	US$ 10.00

Printed in Bangladesh at DOT Printing & Packaging, 164 Shaheed Sayed Nazrul Islam Sarani (Old 3/2), Purana Paltan, Dhaka-1000.

Contents

List of Tables

List of Figures

Abstract

Agglomeration forces are argued to make enterprises in clusters more resilient to shocks than enterprises outside the clusters. We examine this hypothesis in the context of the impact of COVID-19 on small and medium enterprises (SMEs) in Bangladesh. Using a pre-COVID-19 survey as the benchmark, we conducted three rounds of worker-linked surveys of both clustered and non-clustered SMEs. In each post-COVID-19 round, we retrospectively collected data from the previous months, creating two panels of enterprises and workers, spanning February 2020 to February 2021. We observe a V-shape recovery of the SMEs, with a steeper recovery for the clustered SMEs. Controlling for month and firm (workers) fixed effects, in this study, we find no significant differences between SMEs in clusters and SMEs outside during and immediately after the lockdown. However, gaps in output, sales, employment, and inventories between clusters and non-clusters widened over time as the clustered SMEs' recovery was stronger than the non-clustered SMEs. We also documented the differences in Marshallian externalities between clusters and non-clusters and argued that the agglomeration force, particularly sharing and learning, can be an important source of resilience to cope with shocks. Our findings have significant implications for cluster development policies in developing countries.

CHAPTER 1
INTRODUCTION

Firms tend to be located close to each other, which is driven by agglomeration forces (Ellison, Glaeser, & Kerr, 2010; Krugman, 1991) such as increasing returns to scale, externalities, and spatial competition (Fujita & Thisse, 1996). These agglomeration forces have the tendency to form geographical clusters of enterprises endogenously. While the productivity gains, innovations, higher exports, etc. in clusters are well documented empirically (Moretti, 2021; Lall, Shalizi, & Deichmann, 2004; Audretsch & Feldman, 1996), it is not well understood if the agglomeration forces help improve resilience to economic shocks. This question has become increasingly pertinent as a series of shocks of global proportions has shaken the world over the last few decades, including the most recent COVID-19 induced pandemic. However, there is little evidence that firms in clusters are more resilient than those outside clusters, particularly in developed countries (Behrens, Kristian, Boualam & Martin, 2020; Martin, Philippe, Mayer, & Mayneris, 2017). Behrens et al. (2020) used the plant-level Canadian textile and clothing industry from 2001 to 2013, and they observed a substantial decrease in employment and the number of plants due to a surge in imports from China. The most vulnerable clustered plants were found to show some resilience as they were less likely to exit. Similarly, Martin et al. (2017) found that clusters in France are positively associated with higher survival and growth rates (if survived). Still, this association was rather muted during the 2008-09 global financial crisis. In short, the empirical evidence on whether clusters make firms more resilient to shocks is very thin, and the impacts found so far are mostly very modest, if not insignificant.

The present study examines the impact of the COVID-19 induced lockdown on clustered and non-clustered small and medium enterprises (SMEs) and their recovery paths in Bangladesh. The government of Bangladesh announced a nationwide lockdown on 26 March 2020 and ended it on 31 May 2020, which saw a drastic reduction in mobility, industrial production, and employment (World Bank, 2022). We exploited this sudden shock to examine if the firms in clusters are more resilient than those outside to cope with the shock. We followed up on a pre-covid SME survey in 2018 and conducted three more rounds of telephonic surveys during- and post-lockdown periods. Our headline result is that while all SMEs experienced a V-shaped recovery path, the output and employment of clustered SMEs rebounded more strongly than the non-clustered SMEs in the post-lockdown periods.

This study contributes to the very nascent literature on resilient clusters in three major ways. First, the SMEs of Bangladesh offer an interesting case to study. The impact of clusters on resilience is likely to vary with the country's income level, size and types of firms, types of shocks, and so forth. Second, unlike the existing literature, this study examines the impact on small and medium firms in a developing country context, providing new insights into the relationship between agglomeration and resilience. Note that the existing two studies are on Canadian and French firms. Second, studies on clusters are subject to severe challenges of the demarcation of clusters (Delgado, Porter, & Stern, 2016; Fujita & Thisse, 1996). The SME Foundation, a government-run organisation for SME development in Bangladesh, identifies 170 clusters across the country. All the SMEs in a cluster are members of associations of the respective clusters. This cluster membership allows us to distinguish between clustered SMEs and non-clustered SMEs very neatly. Third, our pre-COVID survey conducted in 2018 was designed to study Marshallian externalities. The survey includes specific questions to capture the extent of sharing, matching, and learning externalities. Though we could not follow up on these questions during and after the lockdown,[1] findings from the pre-COVID survey shed important insights into the mechanism of how clusters can lead to better resilience to shocks.

The theory behind how agglomeration forces can lead to higher resilience to shocks is not well developed. This paper focuses on the forces of externalities following Duranton and Puga (2004). Broadly, physical proximity enhances both market and non-market interactions between the firms in clusters, and these interactions can be useful in coping with shocks. Sometimes, informal communication between closely located firms has been argued to have a greater impact than more formal communications (Saxenian, 1994). Information and knowledge sharing are critical in times of crisis, as accurate and greater information on the crisis itself, the government's incentive packages, and effective coping strategies (e.g., strategies on downsising, cost cutting, taking loans, and so on), etc. can help firms survive with higher probability and recover faster. Furthermore, greater market-based interactions such as matching in labour and other input markets due to proximity may place the clustered firms in a better position to deal with any adverse situation. The buyers and sellers in crisis can strike customised contracts, both formal and informal (deferred payments, credits with flexible payment schedules, informal credits, etc.), to cope with the shocks. However, on the other hand, physical proximity can accelerate the contagion of negative effects of shocks. If the firms in clusters are dependent on each other, horizontally and vertically, a few affected firms can impact the whole cluster (Fujita & Thisse, 1996). Hence, the net impact can go either way, and, thus, the cluster's impact on resilience to shock is an open empirical question.

Our major findings are threefold. First, at the firm level, we observe steeper drops in output and employment after the initial shock of lockdown, followed by slower recovery characterised by larger and sharper recovery of output than employment. The faster output and employment recovery indicate that SMEs may have learned to employ workers more efficiently while coping with the shock. Moreover, faster recovery of temporary workers than permanent workers indicates a cost-cutting strategy for SMEs.

[1] The length of the telephonic survey was about 15-20 minutes. We did not want to make the interviews longer and hence decided not to ask the questions on externalities, which were detailed in nature.

Second, the regression results imply that clustered and non-clustered SMEs experienced a sharp drop in output and employment, and clustered SMEs' recovery was stronger than these outside clusters. This is also true for sales and inventories. The recovery varies with the size of SMEs – the larger firms bounced back more sharply than the smaller firms. Additionally, the incidence of reverse migration, that is, the incidence of the workers returned to villages, was lower for the clustered SMEs.

Third, using descriptive statistics from the pre-COVID survey on Marshallian externalities, we find that the incidence of sharing of machines, workers, and transportation was significantly higher for the SMEs in clusters than the SMEs outside. Moreover, business and skill-related information sharing is also higher among the SMEs in clusters. We argue that this sharing in normal times indicates that greater formal and informal interactions between SMEs can help manage shocks better in clusters.

Our study also speaks to two broad strands of literature. First, our study has a strong bearing on the agglomeration literature, focusing on its impact on a set of outcome variables, such as productivity, exports, innovations, etc. (Duranton, Gilles, Martin, Mayer, & Mayneris, 2010; Ciccone & Hall, 1996). Using evidence from the high-tech industries of the USA, Moretti (2021) found significant productivity gains from geographical agglomerations – moving to a city with a large cluster of investors of the same products has been found to increase the number and quality of patents significantly. Kantor and Whalley (2014 and 2019) found significant spillovers from academic research and development (R&D) in regard to local firms. Evidence from developing countries is also robust and substantial. Developing clusters has been an important industrial policy for many developing countries (Sonobe, Tetsushi, & Otsuka, 2011). Ruan and Zhang (2009) showed that an integrated production process was divided into many incremental steps through clustering in China, which significantly increased efficiency. There is ample evidence suggesting that clustering benefits firms in low tech-environment, such as manufacturing in India (Lall et al., 2004), handicrafts in Nairobi (Harris, 2014), and clothing in Peru (Visser, 1999). Our study contributes to this literature by generating evidence on the resilience of clusters in times of crisis.

Second, there is a thick literature on both short and medium-term impacts of COVID-19 on smaller firms both in developed and developing countries. For example, using nationally representative data from the USA, Fairlie (2020) found that more than one-fifth of the small businesses were inactive in April 2020. Developing countries also experienced similar adverse impacts in the initial period of lockdowns, if not worse. A study of 17 developing countries suggests that an overwhelming share of SMEs (94 per cent) were impacted by the pandemic in the case of food supply chains (Nordhagen et al., 2021). Our findings on the initial sharp drops in output, sales, and employment are of a similar magnitude to those found in the cross-country studies. Guerrero-Amezaga et al. (2022) surveyed 35,000 small businesses in eight Latin American countries between March and November 2020, and they found that the pandemic had a significant negative impact on employment. A World Bank study (Cirera et al., 2021) on 38 developing countries documented a set of stylised facts on the patterns of recovery firms' from the pandemic. The recovery process has been found to be highly heterogeneous, and in particular, larger and more productive firms are found to recover faster. Our findings on clustered vs. non-clustered SMEs add to this set of stylised facts – clustered SMEs recovered more strongly than non-clustered SMEs.

There is also increasing interest in the resilience of local, regional, and urban economies (Martin & Sunley, 2015; Martin, 2012). Our study also touches upon this literature on building local economic resilience through agglomeration.

The rest of the report is organised as follows. Chapter 2 sets the context of SMEs in Bangladesh and the spread of COVID-19. Chapter 3 describes surveys, samples, and data used in the study, while chapter 4 provides summary statistics, primarily with graphs. Chapter 5 elaborates on the empirical strategies, and chapter 6 presents the regression results. Chapter 7 shows how impacts vary with firm size, and chapter 8 highlights the potential channels through which clusters might influence resilience to shock. Finally, chapter 9 concludes.

CHAPTER 2
CONTEXT

2.1 SME Clusters in Bangladesh

The Small and Medium Enterprise Foundation (SME Foundation) of the Government of Bangladesh defines the criteria for being a cluster. A cluster produces products or services that are homogenous in nature, but it can have forward and backward linkage industries. The minimum number of establishments has to be 50 located in adjoined areas, such as several villages, wards, unions, or industrial areas. Additionally, the establishments should be located within an area of 5 kilometer radius (SME Foundation, 2013). These SME clusters were endogenously formed; later, the government supported these clusters to grow. Some clusters, such as the Benarashi cluster (a type of saree) of Dhaka district and the light engineering cluster of Pabna district, are more than seventy years old, whereas cricket bat clusters and a few handicrafts clusters grew in the 1990s. Currently, there are 170 SME Foundation registered clusters in Bangladesh.

The sectors such as leather and footwear, light engineering and electronics, garments, hosiery, and handicrafts dominate the SME clusters. These SMEs are family-run, semi-formal (registered with the government but no formal contracts for the workers), and labour-intensive industries. Except for light engineering and electronics, the extent of technological sophistication is meagre – sometimes, a needle is the only capital good used to produce handicrafts. The export amount is negligible from these clusters (Bakht, 2021; Iqbal, Munshi, & Andalib, 2012).

2.2 COVID-19 Cases, Deaths, and Lockdown

Bangladesh reported the first COVID-19 case on 8 March 2020 and the first COVID-19 death on 18 March 2020. The country went on a nationwide lockdown on 26 March 2020, ending on 31 May 2020. The 66-day lockdown period is highlighted in shaded areas in Figures 2.1 and 2.2.

The first wave of COVID-19 cases and deaths kept rising exponentially until July 2020, before the country started experiencing a gradual decline in the numbers. The highest number of COVID-19 deaths on a single day was reported on 30 June 2020 (64 deaths). COVID-19 cases and deaths started declining in July 2020, and the downward trend continued until October 2020. The country saw the next peak (second wave) of cases in December 2020. The numbers started declining again in December 2020, which continued until February 2021. Note that factories were allowed to remain open after one month into the lockdown in 2020.[2]

[2] There was a huge pressure from the businesses, particularly export-oriented RMG sector, to open the factories even during the lockdown. Other sectors also followed the RMG sector, and all factories were allowed to open if adequate safety measures were ensured (Ellis-Petersen & Ahmed, 2020).

Figure 2.1: COVID-19 Cases in Our Sample Period

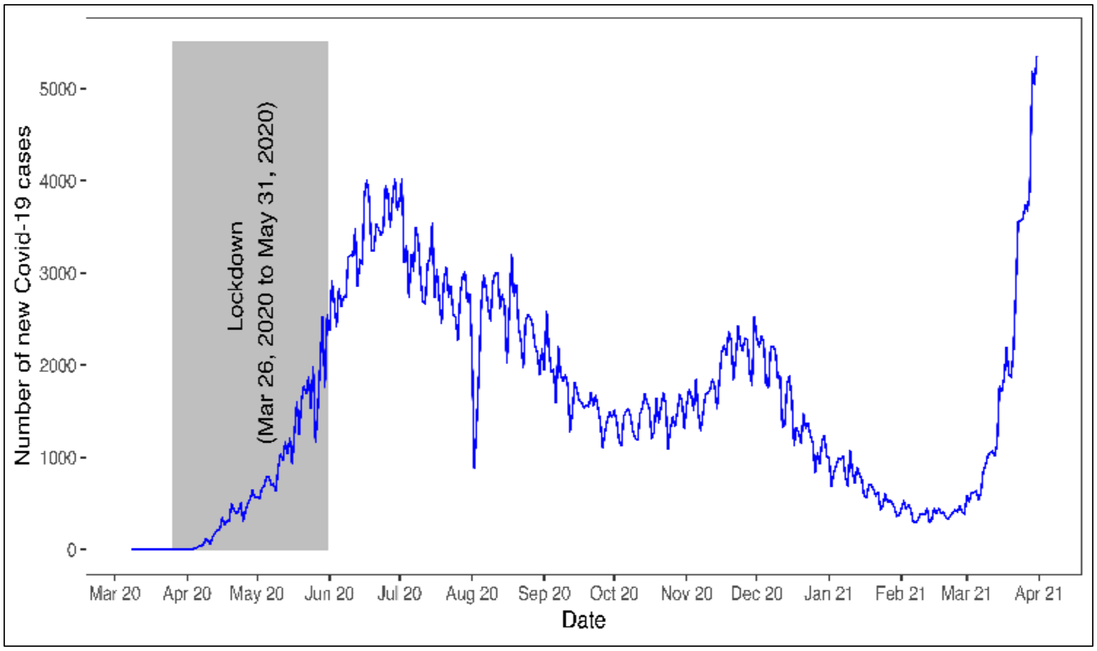
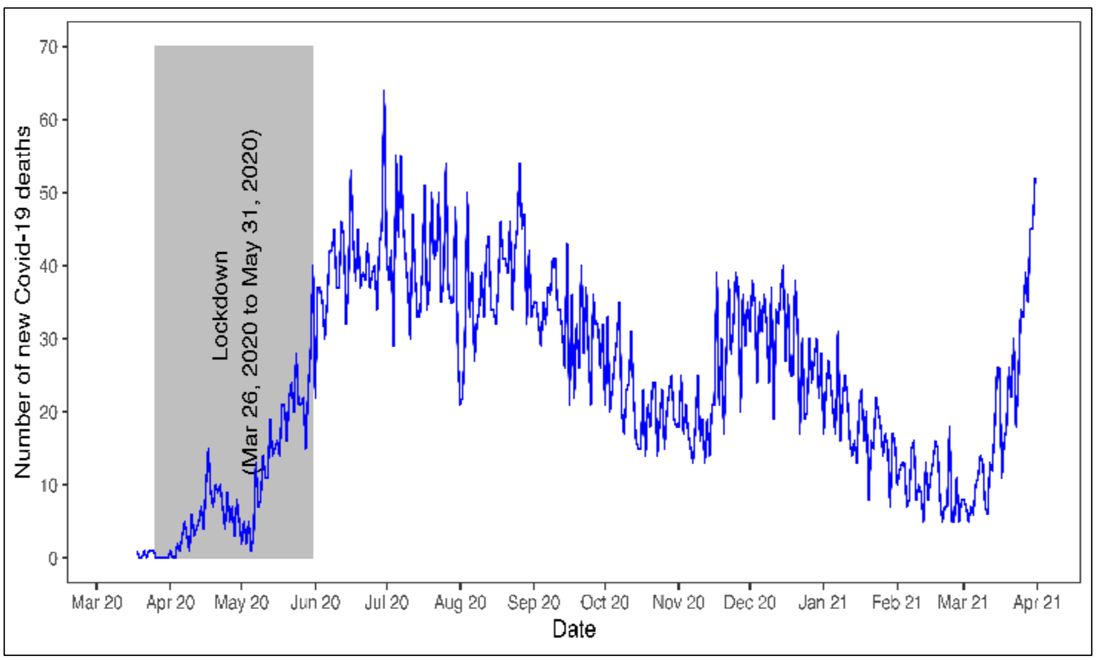
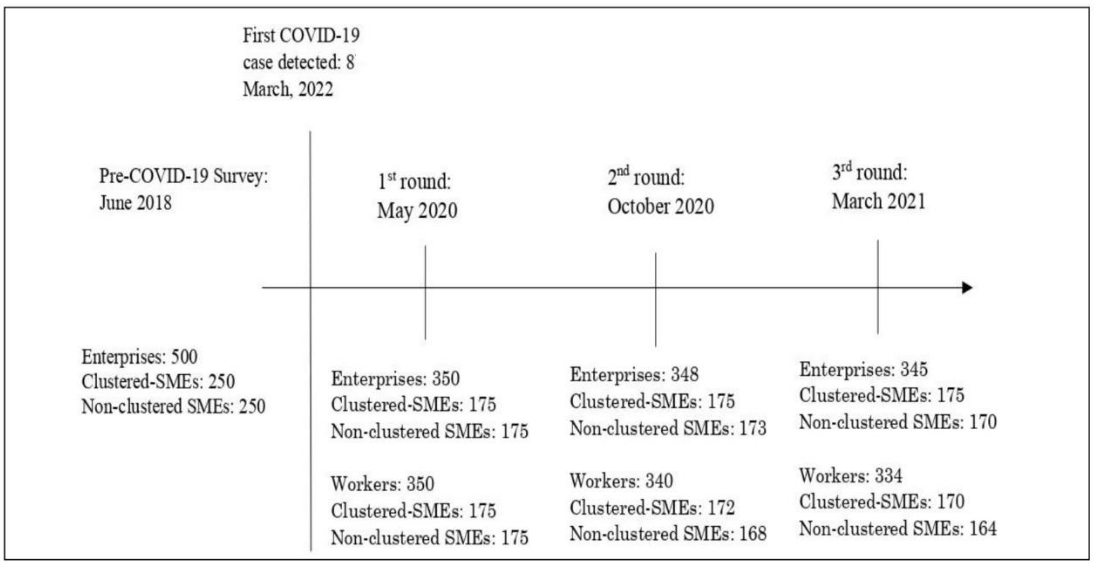


Figure 2.2: COVID-19 Deaths in Our Sample Period



CHAPTER 3
SURVEYS, SAMPLE, AND DATA

The pre-COVID survey, which was conducted in 2018, includes a sample of 500 enterprises–250 of them are in clusters and 250 are outside clusters. Note that the SME Foundation of Bangladesh officially identifies clusters in the country, and there are 170 clusters specialising in different products. There are associations for each cluster, and the association membership helps us distinguish between the clustered and non-clustered SMEs. Note that the pre-COVID sample was drawn from 15 clusters.[3] These clusters produce leather goods, clothing, hosiery, plastic, light engineering, electronics products, cricket bats, embroidered quilts, and perfume/incense. The sample size of each cluster is representative of the respective cluster size.[4]



We revisited this sample and conducted three rounds of telephone surveys, with a four-month interval between each round: 1st round in May 2020, 2nd round in October 2020, and 3rd round in March 2021. In the first round, we successfully interviewed 350 SMEs (175 clustered and 175 non-clustered) and 350 workers (175 clustered and 175 non-clustered), one worker from each enterprise. Note that we had to approach 373 enterprises to reach the sample size of 350. Among 23 these non-responsive enterprises, we found that mobile phones were switched off in 10 cases, and 13 firms declined to be respondents. In order to check if this non-compliance creates any selection problem, we compare the pre-COVID-19 characteristics of our sample (350) with the total sample (500). We did not find any significant difference between these two samples (Table A2 in Appendix), indicating that the non-responsive SMEs are not different from the responsive ones.

[3] The name, location and sample size of each cluster is given in Table A1 in the appendix.
[4] The sample size of each cluster was determined using the formula used by The World Bank's enterprise survey 2013 Bangladesh.

As we know the population size of each cluster from the SME Foundation, we maintained a similar distribution of the cluster-wise SMEs in our telephonic surveys as in the original pre-COVID survey. That is, no cluster is over-represented in our sample. While interviewing the owners or the senior managers of the enterprises, we asked them to provide a name of their workers for the interview. Note that there was no worker survey in the pre-COVID round. This can be subject to selection problems, as the owners could select the names who were more available and/or had better communication skills, for example. To avoid such a problem, we introduced randomness in selecting the workers.[5]

We collected information on three major outcome variables - production, sales, and number of workers in three rounds of surveys. In each survey, we asked for information not only for the previous month but also for the months after the last round of surveys based on recollections. We collected monthly information for February–March 2020 in the first round conducted in May 2020. In the second round, we collected monthly information for May – September 2020, and in the last round, October 2020–February 2021 (Table 3.1). In the second round, due to attrition, we surveyed 348 enterprises (175 clustered and 173 non-clustered SMEs) and 340 workers (172 clustered and 168 non-clustered SMEs). In the final round, we managed to survey 345 enterprises (175 clustered and 170 non-clustered) and 334 workers (170 clustered and 164 non-clustered).

Table 3.1: Three Rounds of Surveys and Sample Size

Rounds	Sample unit	Clustered SMEs	Non-Clustered SMEs	Total	Months Covered
1st	Enterprises	175	175	350	February-April 2020
	Workers	175	175	350	
2nd	Enterprises	175 (0%)	173 (1.14%)	348	May-September 2020
	Workers	172 (1.71%)	168 (4%)	340	
3rd	Enterprises	175 (0%)	170 (2.85%)	345	October 2020 -February 2021
	Workers	170 (2.85%)	164 (6.28%)	334	

Note: Figures in parentheses are the percentage change of sample size compared to the 1st round.

The rate of attrition is low. We lost no enterprise from clustered SMEs and only 1.14 per cent of non-clustered SMEs due to non-compliance and switched-off phones (Table 3.1). However, we do not know if the non-compliance and exit from the market are correlated. In the case of workers, these figures for clustered and non-clustered SMEs are 1.71 and 4 per cent, respectively. In the third round, the attrition rate is 2.85 per cent for the workers of non-clustered SMEs and zero for clustered SMEs, compared to the 1st round. These figures are 2.85 and 6.28 per cent, for the workers of clustered and non-clustered SMEs, respectively.

[5] We follow the following method to select the workers. If the name of the manager or the owner started with letter "A," he/she was asked to give a name of the worker which starts with the following letter "B." If there is no one with a name that starts with the letter "B," the letter "C" was chosen. This process continues until we find a name of a worker, and it did not take us more than 30 seconds to choose a name.

CHAPTER 4
SUMMARY STATISTICS

4.1 Sample Characteristics from Pre-COVID-19 Survey (July 2018)

The advantage of having a pre-COVID survey is that we can use this sample to follow up, which is not affected by COVID itself. This pre-treatment baseline allows us to compare the clustered and non-clustered SMEs before COVID-19. A comparison of the summary statistics of a few basic characteristics of clustered and non-clustered SMEs is given in Table 4.1.

Table 4.1: Pre-COVID (July 2018) Characteristics of the Sample Enterprises

	Full sample	Clustered SME	Non-Clustered SME	Differences (p-values)
Total employment	19.57	21.47	17.83	3.64
	(50.29)	(47.67)	(36.88)	(0.43)
Total output (BDT 100,000)	73.77	81.22	60.22	21.00
	(159.04)	(199.16)	(179.50)	(0.30)
Total sales (BDT 100,000)	68.83	72.89	54.81	18.08
	(184.08)	(198.29)	(181.29)	(0.38)
Capital stock (BDT 100,000)	8.12	11.34	6.66	4.68
	(14.27)	(23.56)	(13.32)	(0.02)
Output-labour ratio (BDT 100,000	3.77	3.78	3.38	0.40
per labour)	(4.9)	(5.39)	(4.11)	(0.44)
Capital-labour ratio (BDT 1,000 per	0.42	0.53	0.37	0.16
labour)	(0.83)	(1.21)	(1.8)	(0.33)

Note: Figures in parentheses are standard deviations for the first three columns. P-values are reported in parentheses in the fourth column.

On average, the non-clustered SMEs are very similar to the clustered SMEs in size and important ratios. The total workers employed are 21 and 18 in clustered and non-clustered SMEs respectively, and the difference is not statistically significant. While the average value of total output produced is higher for clusters than non-clusters (BDT 8.12 million vs. BDT 6.02 million), the difference is again not statistically significant. We find similar results for sales – higher sales for clustered SMEs but not high enough to have a statistically significant difference. However, clustered SMEs use more capital than non-clustered ones (BDT 1.13 million vs. BDT 0.66 million) with statistically significant differences.

To understand how capital and labour were organised to produce output, we report two variables – capital-labour ratio and output-labour ratio. On average, the output-labour ratio was BDT 0.37 million for the full sample, and this figure is slightly higher for the clustered SMEs (BDT 0.38 million) than the non-clustered SMEs (BDT 0.34 million), though the difference is not statistically significant. Interestingly, though clustered SMEs use more capital machinery, their capital-labour ratios are not statistically higher than the non-clustered SMEs.

4.2 Post COVID-19 Enterprise Survey: Impact and Recovery

Figures 4.1 and 4.2 depict the impact and recovery for total output, sales, and employment in the period February 2020-March 2021. Note that there was an immediate fall in these variables when the lockdown was announced, but it started to rebound in April 2020. The extent of the drop is higher for production than sales. However, by the end of March 2021, all three variables rebounded strongly and reached near pre-COVID level, exhibiting a V-shape recovery. Total output is found to recover more than the sales (Figure 2.1). The gap between production and sales tends to increase over time, indicating that the sales recovery was slower than that of output four to five months after the lockdown ended. The initial low level of gaps between production and sales may indicate the settlement of pre-COVID orders.

The drop and recovery of employment are shown in Figure 4.2, with the breakdown of temporary and permanent workers. The drop in jobs was steeper after the initial shock than the increase in employment during the recovery phase, indicating a loss of jobs. This trend is very much in line with the cross-country findings of the World Bank (Cirera et al., 2021). Interestingly, the recovery of output is larger and sharper than employment. This means that the SMEs produced about the same output level with fewer workers, implying higher labour productivity after the shock. The recovery of permanent and temporary employment also indicates that SMEs used more temporary workers than permanent workers during the recovery phase. This use could be a cost-cutting strategy for SMEs to cope with the shock.

Figure 4.1: Monthly Production and Sales

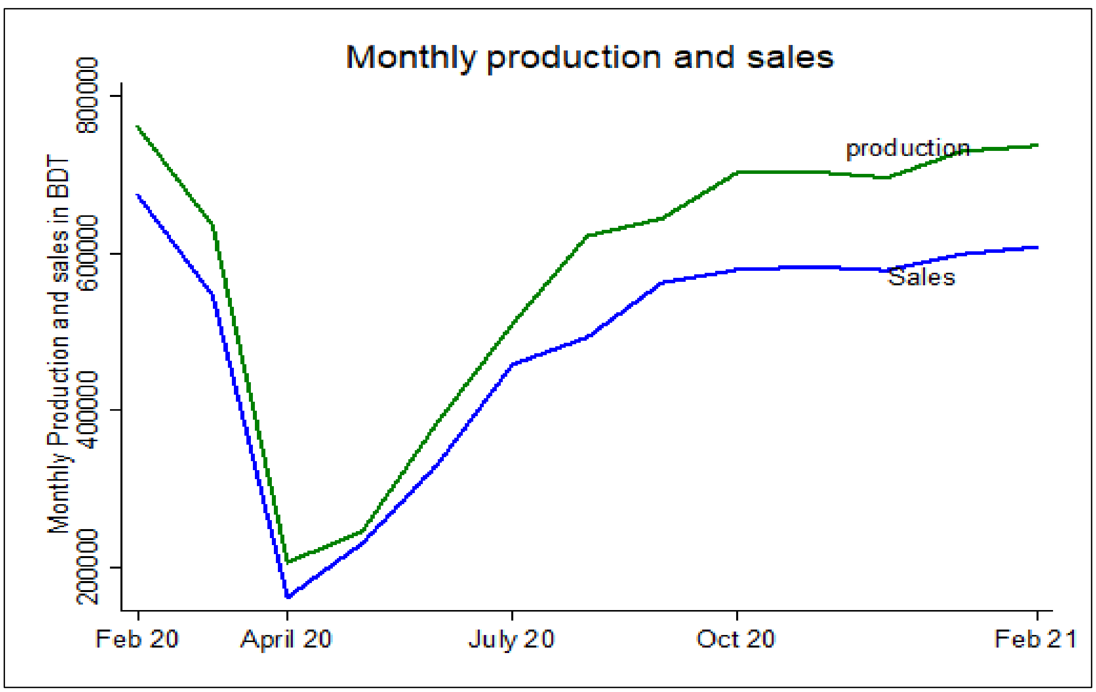
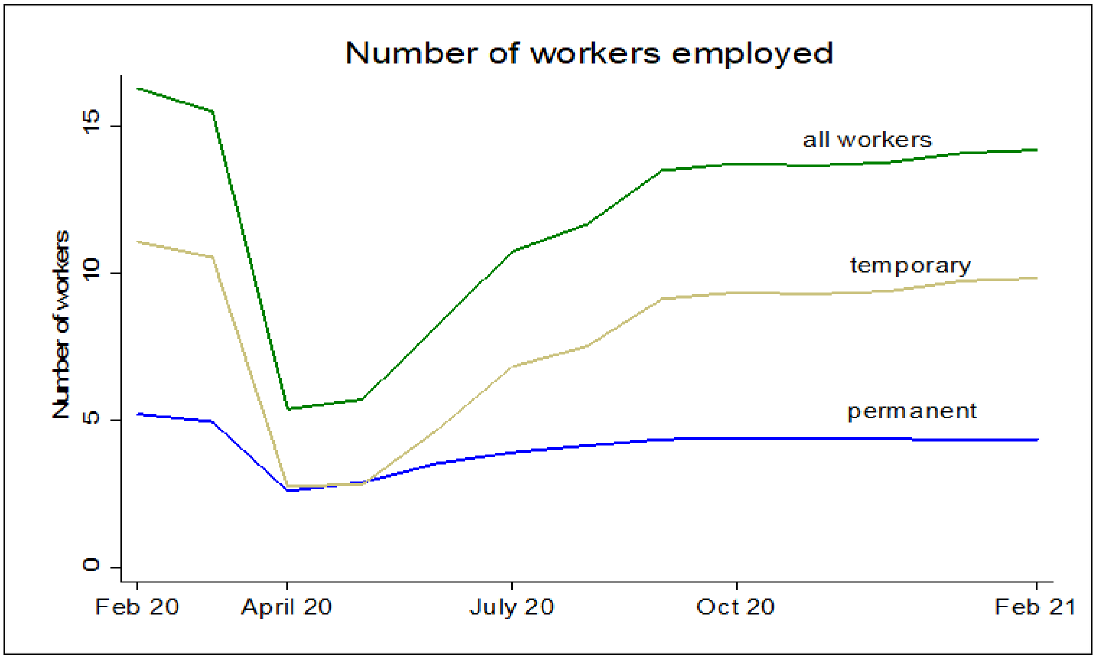


Figure 4.2: Number of Workers Employed



The relative performances of the clustered and non-clustered SMEs are shown in Figures 4.3 and 4.4. The gaps in output and sales between clustered and non-clustered SMEs tended to increase over time. Clustered SMEs managed shocks better in the aftermath of the lockdown –stagnation of sales after October 2020 for the non-clustered SMEs is noteworthy.

Figure 4.3: Monthly Production: Cluster vs Non-cluster

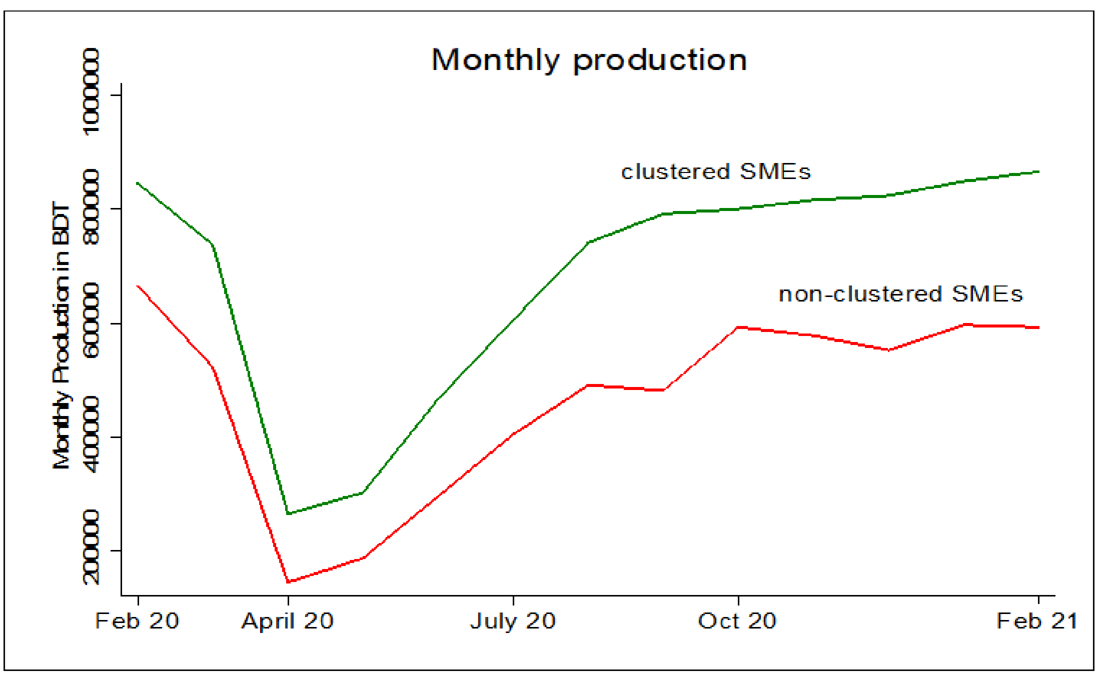
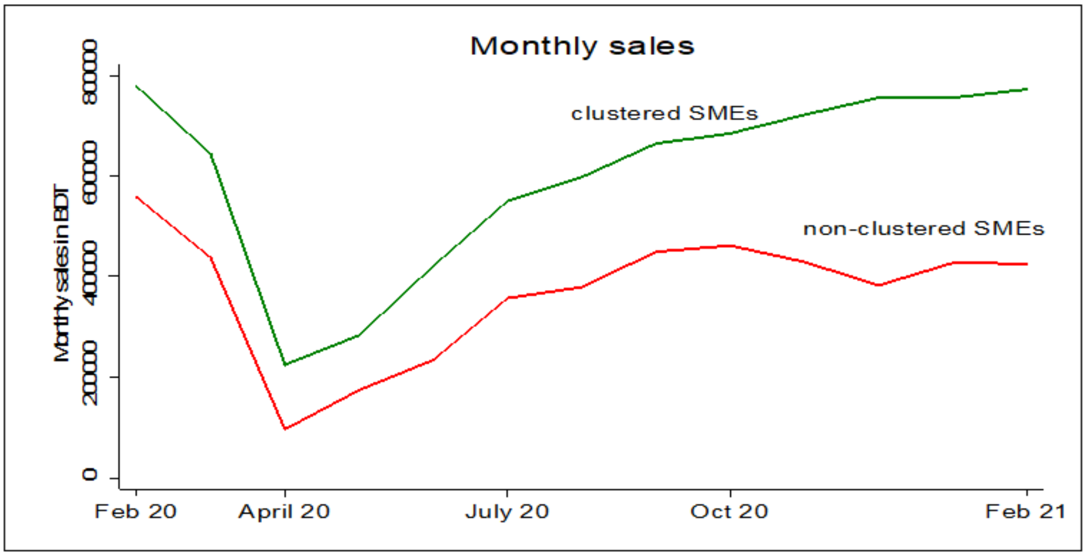
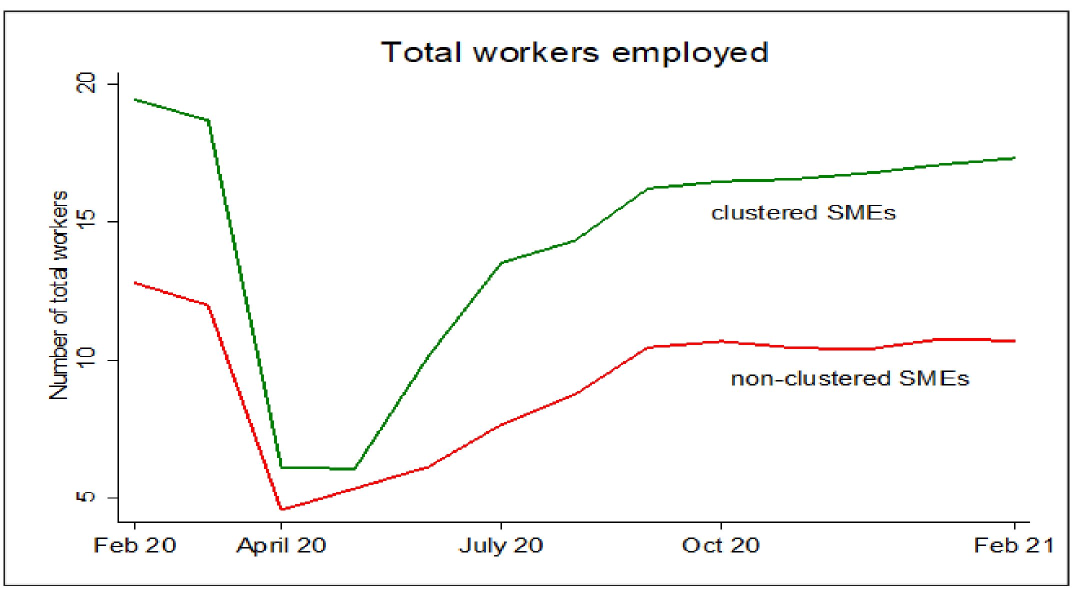


Figure 4.4: **Monthly Sales: Cluster vs Non-cluster**



We plot total, permanent, and temporary workers for clustered and non-clustered SMEs in Figures 4.5–4.7. Note that the drop in total workers was larger for the clustered SMEs than the non-clustered SMEs – from 19 workers to 6 workers in the case of clustered SMEs, while it was from 12.5 to 4.5 workers for non-clustered SMEs. However, it does not necessarily mean that the workers were laid off – both production and employment could be temporarily suspended.[6] However, the recovery of employment - getting workers back to work – was much quicker for the clustered SMEs.

Figure 4.5: Total Workers Employed



[6] Note that there is hardly any formal written contract for the workers in SMEs (Asian Development Bank, 2012). The informal contracts are verbal in nature and allow temporary suspension to be executed without any legal or financial implications.

Figure 4.6: Permanent Workers Employed

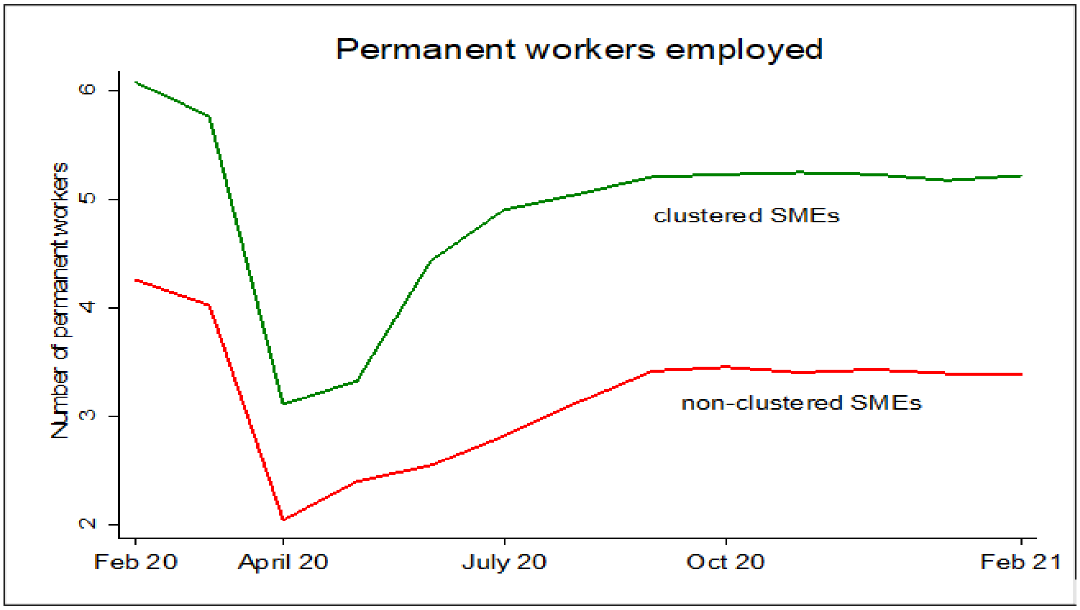
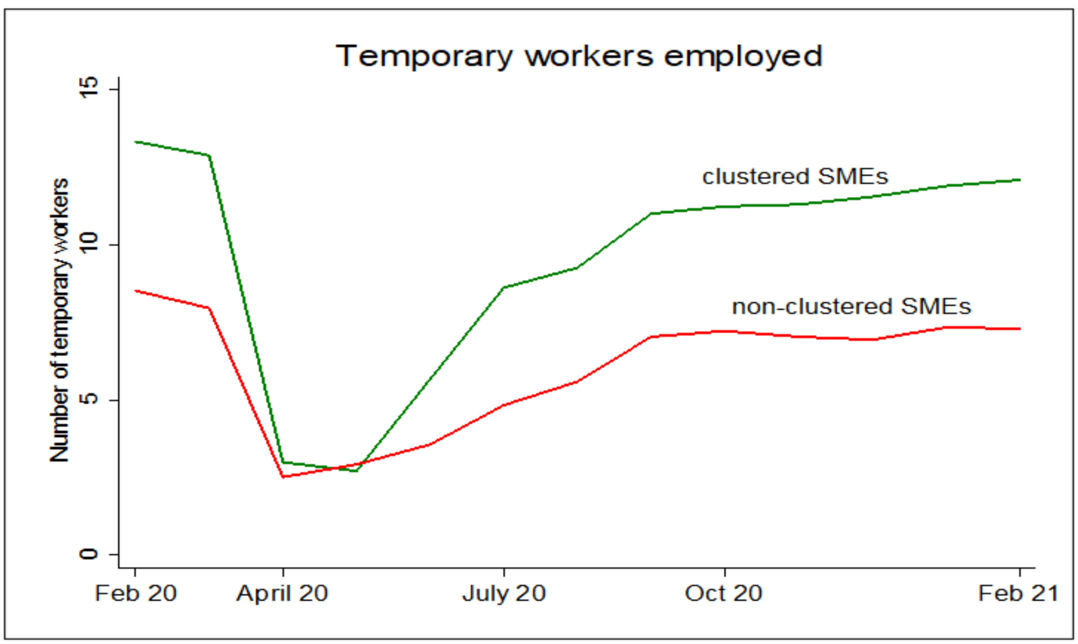


Figure 4.7: Temporary Workers Employed



4.3 Post COVID-19 Worker Survey: Impact and Recovery

Now, we turn to the worker survey. To reiterate, we sample one worker from each enterprise. In Figure 4.8, we express the number of workers employed in a month as a percentage of the number of workers in February 2020 (pre-COVID month). The figure shows a more than 80 per cent drop in the number of workers in April 2020 but rebounded very sharply. The share of workers in clustered SMEs surpassed the pre-COVID level, but the share of workers in non-clustered SMEs fell short of the pre-covid level. Moreover, the share of workers who went to their villages during and post-lockdown months is low (Figure 4.9).

Figure 4.8: Share of Employed Workers

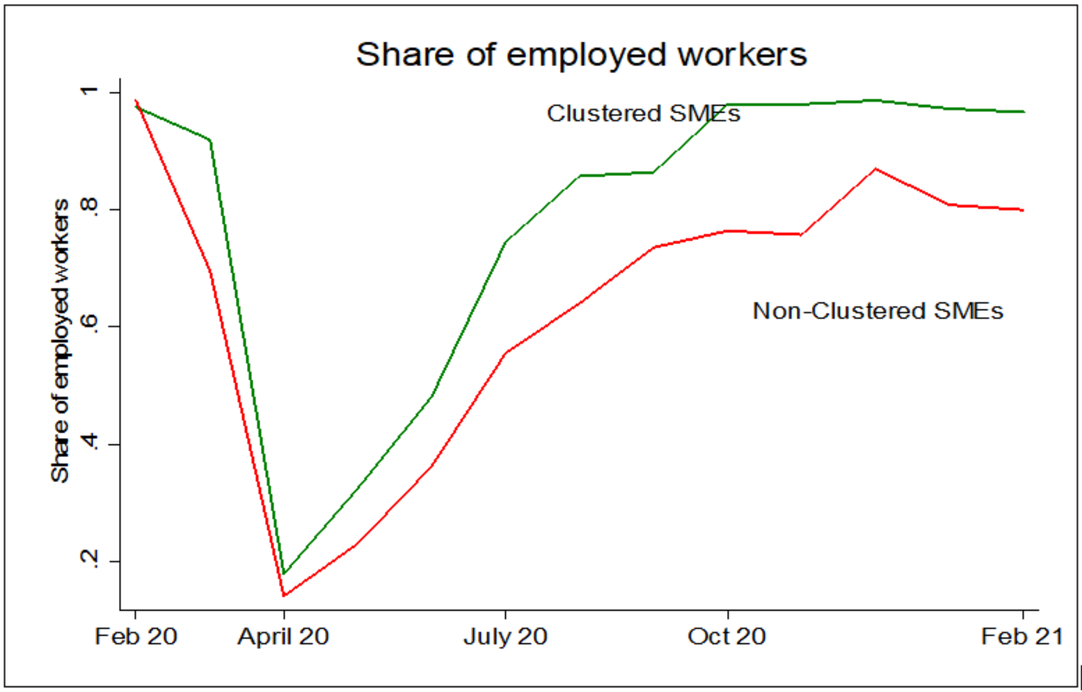
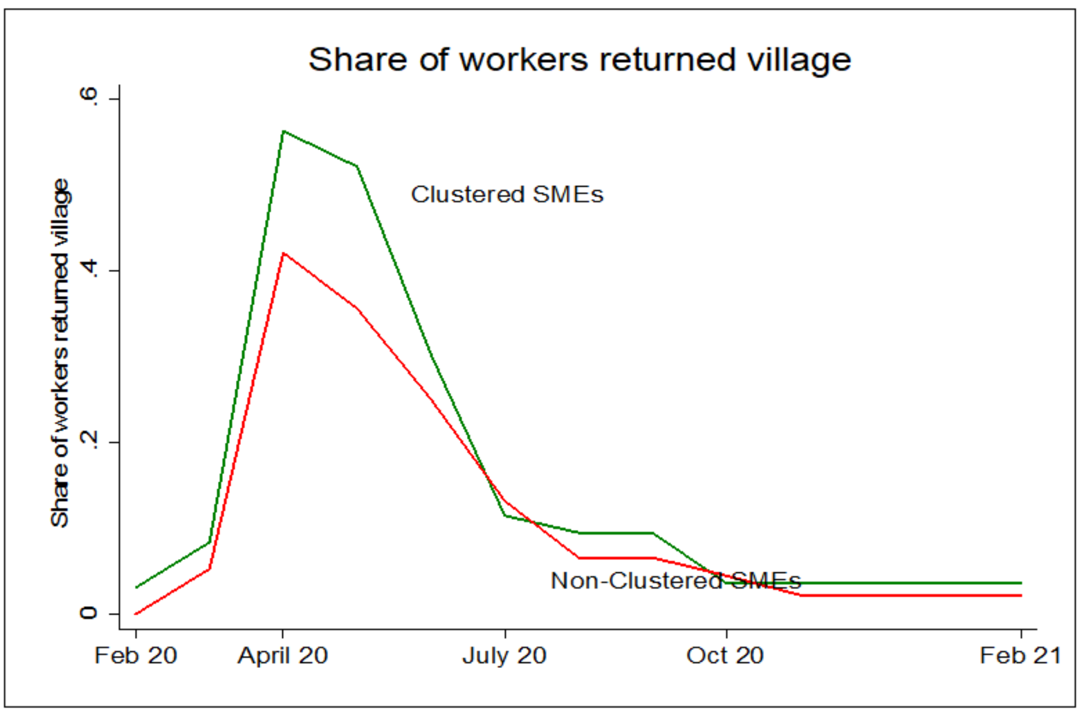


Figure 4.9: Share of Workers Who Returned to the Village



The monthly salary received by the workers tended to reach the pre-COVID levels. However, the gap between average monthly salary received increased over time, with a large drop for non-clustered SMEs towards the end of the sample period. We also plot the monthly household income of the workers of both clustered and non-clustered SMEs. Interestingly, the gap between cluster and non-cluster was smaller for household income than the workers' salary itself. This gap indicates that households had other means to cope with the shocks, such as assistance from the government, NGOs, and other informal sources, as evident in Table 8.4.

Figure 4.10: Monthly Salaries Received by Workers

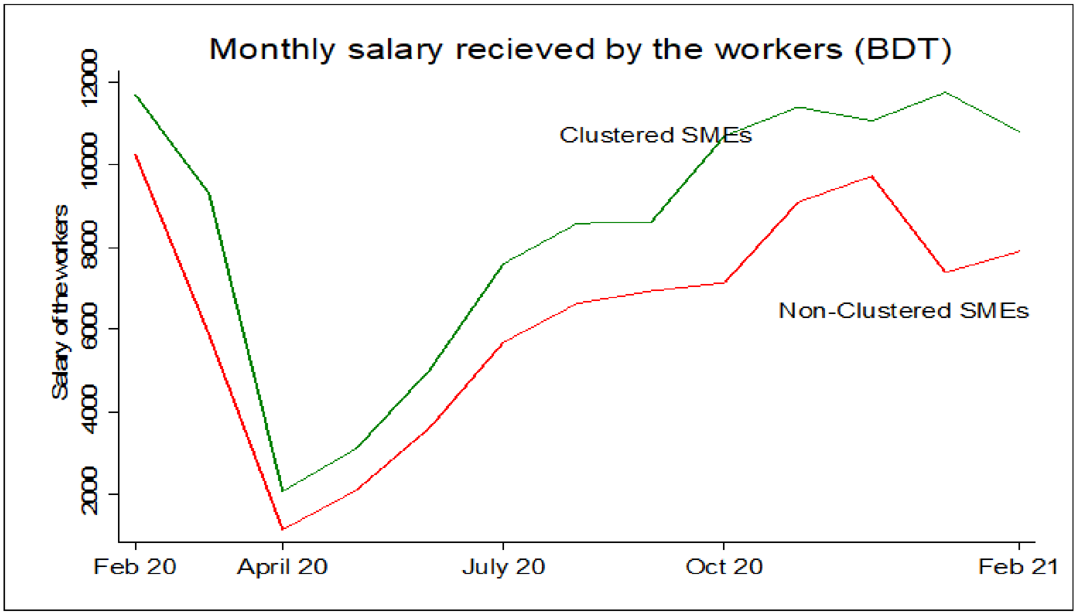
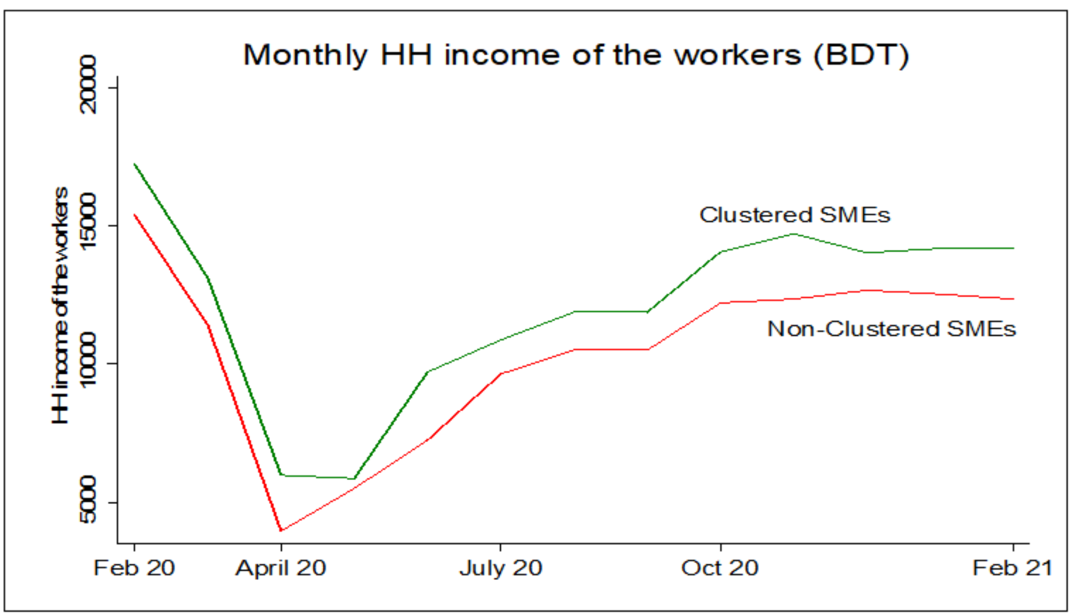


Figure 4.11: Monthly Household Income of the Workers



CHAPTER 5
EMPIRICAL STRATEGIES

While we document a set of observations in the previous section, the differences in the outcome variables between cluster and non-cluster SMEs may not be statistically significant when we control for other unobserved characteristics of the enterprises. The entrepreneurial ability of the clustered SMEs might be higher, which we cannot observe. There are selection problems here too – the SMEs that have endogenously grown into a cluster might be different from those of non-clustered SMEs.

It is not feasible to randomise firms into clusters and non-clusters. At best, we can run firm fixed effects to exploit within-firm variations over months. We also control for month-year fixed effects to neutralise month-specific heterogeneity that might confound the results. To capture the month-wise impacts of being in a cluster on the outcome variables, we interact a cluster dummy with month. The cluster dummy assumes 1 if an SME belongs to a cluster and 0 otherwise. The interaction terms capture the impact of being in a cluster compared to non-cluster SMEs, controlling for firm and month-fixed effects. The regression model we estimate is the following (where *i* denotes SMEs and *t* months):

$$Outcome_{it} = \alpha_0 + \alpha_1 Firm\ FEs_i + +\alpha_2 Month\ FEs_t + \alpha_3 Cluster\ x\ Month\ FEs_{it} + u_{it} \qquad (1)$$

Here, the outcome variables are production, sales, inventory (production minus sales), total workers employed, permanent workers employed, temporary workers employed, and anxiety level of the owners/managers. These variables are from the enterprise survey. Some months may experience higher production or sales in the clustered SMEs than the non-clustered SMEs due to factors completely unrelated to agglomeration, and we may wrongly attribute it to the clusters. We captured this unobserved heterogeneity using month FEs. Moreover, enterprises located in clusters may be characteristically different from those outside the clusters. Hence, we used firm FEs to exploit within-firm variations. Our coefficient of interest is α_3, the coefficient of the interaction term between the cluster and month dummies. This coefficient shows how outcome variables for the clustered SMEs change with months compared to non-clustered SMEs, controlling for firm and month FEs.

In the case of worker-level variables, the outcome variables are monthly salary, monthly household income, the extent of hardship, and whether the workers returned to villages. In this case, we estimate the following model.

$$Outcome_{it} = \beta_0 + \beta_1 Worke\ FEs_i + +\beta_2 Month\ FEs_t + \beta_3 Cluster\ x\ Month\ FEs_{it} + \varepsilon_{it} \qquad (2)$$

We asked the owners and the workers to scale the degree of anxiety and hardship respectively on a 1-10 scale, with higher values signifying a higher level of anxiety and hardship.

CHAPTER 6
REGRESSION RESULTS

6.1 Results on Enterprise and Aggregate Workers (Enterprise Survey)

Table 6.1 presents the regression results of the regression model (1) specified in chapter 5. These results are for enterprise-level monthly outcomes–production, sales, differences between production and sales (inventories), and anxiety of the managers/owners. Note that we rescaled the outcome variables and expressed them as a percentage of the value of the pre-covid month (February 2020). Hence, the coefficients of the regression models 1 and 2 imply the differences in outcome variables between the clustered and non-clustered SMEs in relation to the pre-covid month. Consider the coefficient of Cluster x July 2020 when the dependent variable is monthly production (column 1). This coefficient is 0.187, which is also statistically significant at a 1 per cent level. This coefficient implies that the production of clustered SMEs in July 2020 compared to February 2020 was 18.7 per cent higher than that of non-clustered SMEs.

Table 6.1: Impact on Firms (Enterprise Survey)

Variables	(1)	(2)	(3)	(4)
	Production	Sales	Inventory	Anxiety
Cluster x March 2020	0.070	0.270	0.027	-0.058
	(0.074)	(0.177)	(0.135)	(0.110)
Cluster x April 2020	0.062	0.092	0.120*	0.009
	(0.053)	(0.075)	(0.066)	(0.123)
Cluster x May 2020	0.004	0.041	0.096	0.016
	(0.057)	(0.084)	(0.069)	(0.115)
Cluster x June 2020	0.075	0.056	0.077	-0.058
	(0.061)	(0.084)	(0.054)	(0.109)
Cluster x July 2020	0.187**	0.150	0.133*	-0.021
	(0.081)	(0.104)	(0.073)	(0.113)
Cluster x August 2020	0.177*	0.188*	0.115	-0.196**
	(0.100)	(0.102)	(0.082)	(0.088)
Cluster x September 2020	0.386***	0.185	0.393**	-0.169*
	(0.106)	(0.193)	(0.190)	(0.089)
Cluster x October 2020	0.258**	0.281**	0.180	-0.095
	(0.103)	(0.115)	(0.145)	(0.092)
Cluster x November 2020	0.063	0.402***	-0.183	-0.188**
	(0.193)	(0.116)	(0.177)	(0.093)
Cluster x December 2020	0.074	0.441***	-0.428*	-0.218***
	(0.160)	(0.142)	(0.254)	(0.080)
Cluster x January 2021	0.297***	0.606***	-0.142	-0.278***
	(0.107)	(0.138)	(0.110)	(0.082)
Cluster x February 2021	0.155	0.621***	-0.297*	-0.255***
	(0.161)	(0.117)	(0.166)	(0.078)
Month-Year FEs	Yes	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes	Yes
Constant	1.008***	0.958***	0.153***	1.000***
	(0.024)	(0.035)	(0.031)	(0.034)
Observations	2,199	2,146	2,199	2,238
R-squared	0.311	0.255	0.036	0.632
Number of Firms	344	336	336	344

Note: Robust standard errors clustered at the firm level are reported in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

The regression results show that there were no differences in output between the clustered and non-clustered SMEs during and immediately after lockdown, compared with the pre-COVID level (column 1). The differences started to manifest from July 2020 and became stronger towards the end of 2020 – clustered SMEs outperformed non-clustered ones. In the month of January 2021, the difference in output compared to February 2020 was about 30 per cent.

In the case of sales, SMEs experienced a much stronger recovery than non-clustered SMEs (column 2). All the coefficients after October 2020 are highly significant, and in the last two months - January 2021 and February 2021 – the relative sales (relative to February 2020) for the clustered SMEs were about 60 per cent higher than the non-clustered SMEs.

Inventory is an important outcome variable, as the literature suggests that the slow-down of businesses due to the pandemic has resulted in the piling of inventory in many countries (Howland, 2020). The regression results indicate that the monthly inventory, as defined by monthly production minus monthly sales, tended to be lower for the clustered SMEs towards the end of the sample period (column 3). In February 2021, the inventory was about 30 per cent lower for the clustered SMEs, though the coefficient is significant only at a 10 per cent level.

Results on the anxiety variable also show that owners of clustered SMEs suffered less anxiety than those of non-clustered SMEs during recovery. The statistically significant differences are observed from August 2020, and these differences are consistent with the output, sales, and inventory results in columns 1-3.

Table 6.2: Impact on Aggregate Workers (Enterprise Survey)

Variables	(1)	(2)	(3)
	Total Workers	Permanent Workers	Temporary Workers
Cluster x March 2020	0.015	0.084	-0.054
	(0.041)	(0.057)	(0.053)
Cluster x April 2020	-0.028	0.065	-0.039
	(0.064)	(0.084)	(0.074)
Cluster x May 2020	-0.116*	0.049	-0.168**
	(0.062)	(0.078)	(0.073)
Cluster x June 2020	0.042	0.208***	0.003
	(0.062)	(0.073)	(0.077)
Cluster x July 2020	0.064	0.168**	0.005
	(0.056)	(0.072)	(0.072)
Cluster x August 2020	0.015	0.078	-0.010
	(0.053)	(0.066)	(0.061)
Cluster x September 2020	0.066	0.019	-0.004
	(0.069)	(0.091)	(0.095)
Cluster x October 2020	0.113	0.063	0.052
	(0.073)	(0.102)	(0.095)

(Contd. Table 6.2)

Variables	(1)	(2)	(3)
	Total Workers	Permanent Workers	Temporary Workers
Cluster x November 2020	0.136**	0.010	0.153**
	(0.061)	(0.107)	(0.073)
Cluster x December 2020	0.123*	0.126	0.089
	(0.063)	(0.102)	(0.077)
Cluster x January 2021	0.156**	0.114	0.170**
	(0.062)	(0.102)	(0.081)
Cluster x February 2021	0.234***	0.162	0.219***
	(0.064)	(0.108)	(0.083)
Month-Year FEs	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes
Constant	0.997***	1.001***	0.987***
	(0.016)	(0.023)	(0.019)
Observations	2,192	1,444	1,561
R-squared	0.405	0.169	0.428
Number of workers	343	228	239

Note: Robust standard errors clustered at the firm level are reported in parentheses.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 6.2 presents the regression results for the aggregate employment variables collected from the enterprise surveys. In this case, we also express the outcome variables as the percentage of the values in the pre-COVID month (February 2020). The first dependent variable is the month-wise total employment of the enterprises compared to February 2020 (column 1). Again, we find that there were no significant differences in total workers between the clustered SMEs and non-clustered SMEs during and immediately after the lockdown. While the lockdown ended in May 2020, the differences in total employment first showed up in November 2020. The clustered SMEs employed more workers over time than the non-clustered SMEs, while they were recovering. In November 2020, the ratio of total employment in November to employment in February 2020 was about 13.6 per cent higher for the clustered SMEs. This figure increased to 23.4 per cent in February 2021. This increase in employment for clustered SMEs is consistent with the finding that output also increased toward the end of the sample period.

Interestingly, it is the temporary workers that increased, not the permanent workers. Column 2 presents the regression results for the permanent workers. There was no month-wise difference between the clustered and non-clustered SMEs for the permanent workers (column 2). However, in the case of temporary workers, we observe a significantly higher number of workers for the clustered SMEs towards the end of November 2020 (column 3). The percentage of temporary workers in February 2021 compared to February 2020 was about 21.9 per cent higher for clustered SMEs than non-clustered ones. The recovery of the clustered SMEs is characterised by employing more temporary workers (column 3).

6.2 Results on Individual Workers (Worker Survey)

Now, we turn to the worker survey. Table 6.3 presents the regression results for monthly salary, household income, economic hardship, and whether the workers returned to villages. We also rescaled these variables by expressing them in terms of percentages of respective values in the pre-COVID month (February 2020). Results relating to salary show that there was no difference in month-wise salary (relative to February 2020) for the clustered and non-clustered SMEs, nor in the case of household income. However, the workers from clustered SMEs reported substantially less economic hardship than those from non-clustered SMEs. Interestingly, the extent of hardship was significantly lower for all months for the clustered SMEs than for the non-clustered SMEs.

Table 6.3: Impact on Workers (Worker Survey)

Variables	(1)	(2)	(3)	(4)
	Salary	Income	Hardship	Returned Village
Cluster x March 2020	0.052	0.085	-0.552**	-0.006
	(0.079)	(0.094)	(0.269)	(0.019)
Cluster x April 2020	0.011	0.189	-0.878**	0.092*
	(0.061)	(0.164)	(0.339)	(0.054)
Cluster x May 2020	0.027	-0.246	-0.812**	-0.104**
	(0.069)	(0.150)	(0.331)	(0.052)
Cluster x June 2020	-0.007	-0.019	-0.507	0.021
	(0.081)	(0.085)	(0.557)	(0.045)
Cluster x July 2020	-0.071	0.056	-0.864***	-0.025
	(0.091)	(0.076)	(0.299)	(0.029)
Cluster x August 2020	-0.082	0.068	-1.071***	-0.178
	(0.116)	(0.075)	(0.297)	(0.232)
Cluster x September 2020	-0.044	0.025	-0.677	-0.178
	(0.119)	(0.079)	(0.501)	(0.232)
Cluster x October 2020	0.008	-0.025	-1.371***	-0.569***
	(0.088)	(0.098)	(0.271)	(0.188)
Cluster x November 2020	-0.113	-0.028	-1.491***	-0.551***
	(0.148)	(0.116)	(0.321)	(0.189)
Cluster x December 2020	-0.055	-0.027	-1.363***	-0.528***
	(0.113)	(0.114)	(0.262)	(0.189)
Cluster x January 2021	0.229	0.069	-1.095***	-0.527***
	(0.180)	(0.108)	(0.317)	(0.191)
Cluster x February 2021	-0.166	0.000	-1.482***	-0.612***
	(0.109)	(0.104)	(0.289)	(0.194)
Month-Year FEs	Yes	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes	Yes
Constant	0.991***	1.006***	1.040***	1.337***
	(0.021)	(0.022)	(0.094)	(0.034)
Observations	2,165	1,951	1,997	3,458
R-squared	0.227	0.208	0.204	0.039
Number of workers	314	288	314	311

Note: Robust standard errors clustered at the worker level are reported in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Evidence shows that COVID-19 induced pandemic led to reverse migration from urban to rural areas (Dandekar & Ghai, 2020). Anecdotal evidence suggests that many workers working in the urban areas returned to their villages during lockdowns, and a fraction stayed back there as the enterprises winded up or shredded workers. The regression results show that the incidence of returning to the village was lower for the workers in clusters than outside clusters.

CHAPTER 7
HETEROGENEITY OF IMPACTS

The impact of clusters on the outcome variables is likely to vary with firm size. Hence, we split the sample into large and small enterprises based on the median value of the 2018 sample. Columns 1 and 2 of Table 7.1 present the results for large and small enterprises, with production being the dependent variable. We observed several significant impacts during mid-2020 as well as in February 2021 for the large firms. On the other hand, there is hardly any significant positive impact for small firms with a couple of negative coefficients. Broadly, the recovery is more pronounced for larger firms than for smaller firms. However, in the case of sales (columns 3 and 4), the smaller SMEs are found to recover more robustly than the larger SMEs. This could be due to a lower amount of inventory held by the smaller SMEs. We found that inventory in February 2021 relative to February 2020 was about 27 per cent lower for the smaller SMEs in clusters. Interestingly, the anxiety level of the smaller clustered SMEs is found to be lesser than the larger ones (columns 7 and 8). We observe a greater number of months with significant negative coefficients for smaller clustered SMEs.

Table 7.1: Impact on Production and Sales by SME Size

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Prod. Large	Prod. Small	Sales Large	Sales Small	Inv. Large	Inv. Small	Anxiety Large	Anxiety Small
Cluster x March 2020	-0.105	0.029	-0.160	0.480	0.057	-0.180	-0.101	-0.022
	(0.082)	(0.080)	(0.243)	(0.311)	(0.222)	(0.185)	(0.205)	(0.169)
Cluster x April 2020	0.032	-0.013	0.229	0.108	-0.090	-0.065	-0.149	-0.224
	(0.087)	(0.076)	(0.145)	(0.118)	(0.106)	(0.094)	(0.189)	(0.218)
Cluster x May 2020	0.109	-0.174*	0.200	-0.202	0.028	-0.029	-0.001	-0.066
	(0.092)	(0.095)	(0.167)	(0.144)	(0.103)	(0.109)	(0.205)	(0.159)
Cluster x June 2020	-0.004	-0.085	-0.214	0.052	0.329	-0.112	-0.094	-0.215
	(0.095)	(0.091)	(0.324)	(0.133)	(0.287)	(0.093)	(0.185)	(0.145)
Cluster x July 2020	0.240***	-0.214**	0.122	-0.108	0.180	-0.136	-0.016	-0.073
	(0.091)	(0.084)	(0.142)	(0.132)	(0.109)	(0.091)	(0.205)	(0.145)
Cluster x August 2020	0.258*	-0.187*	-0.085	-0.061	0.374	-0.028	-0.197	-0.246
	(0.154)	(0.109)	(0.261)	(0.148)	(0.232)	(0.115)	(0.207)	(0.153)
Cluster x September 2020	0.459***	0.347*	-0.021	0.431*	0.458	0.011	-0.057	-0.211
	(0.153)	(0.181)	(0.346)	(0.236)	(0.307)	(0.121)	(0.142)	(0.141)
Cluster x October 2020	0.247	0.115	0.047	0.362**	0.161	-0.149	-0.118	-0.249*
	(0.150)	(0.135)	(0.224)	(0.174)	(0.175)	(0.140)	(0.144)	(0.138)
Cluster x November 2020	0.217	-0.066	0.094	0.586**	0.062	-0.422	-0.141	-0.409***
	(0.141)	(0.362)	(0.250)	(0.259)	(0.164)	(0.332)	(0.143)	(0.151)
Cluster x December 2020	0.241	0.178	1.157	0.688**	-0.891	-0.341	-0.155	-0.422***
	(0.153)	(0.156)	(0.918)	(0.296)	(0.855)	(0.217)	(0.133)	(0.136)
Cluster x January 2021	0.238	0.075	0.081	0.481**	0.071	-0.064	-0.177	-0.475***
	(0.151)	(0.131)	(0.254)	(0.213)	(0.149)	(0.313)	(0.133)	(0.143)
Cluster x February 2021	0.355**	0.107	0.268	0.472**	-0.033	-0.268**	-0.193*	-0.539***
	(0.159)	(0.119)	(0.298)	(0.223)	(0.153)	(0.128)	(0.116)	(0.162)
Constant	1.008***	1.009***	1.017***	0.975***	0.105*	0.167***	0.995***	1.008***
	(0.035)	(0.030)	(0.071)	(0.059)	(0.055)	(0.044)	(0.059)	(0.052)
Month-Year FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,137	982	1,125	Yes	Yes	Yes	1,169	1,018
R-squared	0.338	0.415	0.086	0.303	0.026	0.032	0.574	0.634
Number of SMEs	176	168	174	162	176	168	181	172

Note: Robust standard errors clustered at the firm level are reported in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Table 7.2: Impact on Workers by Size of SMEs

Variables	(1) Total Workers Large	(2) Total Workers Small	(3) Permanent Workers Large	(4) Permanent Workers Small	(5) Temporary Workers Large	(6) Temporary Workers Small
Cluster x March 2020	-0.020	0.094	0.008	0.074	-0.019	-0.011
	(0.047)	(0.069)	(0.054)	(0.093)	(0.066)	(0.100)
Cluster x April 2020	-0.018	-0.124	0.068	0.025	-0.093	-0.182*
	(0.095)	(0.092)	(0.127)	(0.122)	(0.120)	(0.106)
Cluster x May 2020	-0.063	-0.274***	0.045	-0.046	0.008	-0.389***
	(0.088)	(0.093)	(0.112)	(0.111)	(0.112)	(0.115)
Cluster x June 2020	0.022	-0.169*	0.185*	0.052	-0.034	-0.249**
	(0.081)	(0.088)	(0.094)	(0.111)	(0.113)	(0.111)
Cluster x July 2020	0.177**	-0.156*	0.225**	0.011	0.135	-0.256**
	(0.076)	(0.082)	(0.092)	(0.101)	(0.093)	(0.104)
Cluster x August 2020	0.071	-0.151*	0.080	-0.012	0.052	-0.150
	(0.073)	(0.080)	(0.078)	(0.128)	(0.103)	(0.100)
Cluster x September 2020	0.148**	0.036	-0.017	-0.083	0.087	0.065
	(0.070)	(0.093)	(0.104)	(0.168)	(0.095)	(0.137)
Cluster x October 2020	0.115*	-0.003	-0.021	0.045	0.014	0.031
	(0.068)	(0.117)	(0.098)	(0.225)	(0.097)	(0.114)
Cluster x November 2020	0.096	-0.018	-0.058	-0.034	0.055	0.082
	(0.080)	(0.112)	(0.110)	(0.196)	(0.099)	(0.113)
Cluster x December 2020	0.156**	0.049	-0.119	0.067	0.171	0.074
	(0.079)	(0.098)	(0.104)	(0.186)	(0.111)	(0.121)
Cluster x January 2021	0.188**	-0.001	-0.053	-0.054	0.311**	0.011
	(0.077)	(0.136)	(0.112)	(0.194)	(0.147)	(0.179)
Cluster x February 2021	0.139*	-0.077	0.050	-0.158	0.182*	0.069
	(0.074)	(0.129)	(0.111)	(0.216)	(0.097)	(0.115)
Constant	0.997***	1.006***	1.007***	1.008***	0.988***	1.007***
	(0.019)	(0.023)	(0.025)	(0.040)	(0.025)	(0.027)
Month-Year FEs	Yes	Yes	Yes	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,136	982	833	629	773	673
R-squared	0.365	0.392	0.205	0.197	0.365	0.449
Number of firms	176	167	128	100	122	117

Note: Robust standard errors clustered at the firm level are reported in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Table 7.2 presents the regression results for the total employment by firm size. The employment of the larger clustered SMEs is found to recover more robustly than the smaller clustered SMEs. Significant and positive impacts are found from July 2020 for the larger SMEs (column 1), whereas we observe a number of negative impacts for smaller SMEs (column 2), mainly in the first half of 2020. Broadly, we did not find any significant impact for the permanent or temporary workers varying with firm size. However, in the case of smaller SMEs (column 6), smaller clustered SMEs are found to employ fewer temporary workers than the non-clustered SMEs in the recovery phase.

CHAPTER 8
SOURCES OF RESILIENCE: MARSHALLIAN EXTERNALITIES

Note that we collected data on the extent of sharing, matching, and learning in the pre-COVID survey in 2018 for both clustered and non-clustered samples. We could not collect information on externalities in the following three rounds as the latter rounds were short telephone surveys. However, since the sample is the same, we use the insights from the first round to shed some light on the potential sources of agglomeration forces that might impact the resilience of SMEs in clusters, following Duranton and Puga (2004).

8.1 Sharing

Physical proximity allows firms to share indivisible goods and thus helps reduce production costs. Firms can also share skilled workers, which is expensive for a single firm. Firms are also found to pool transports for both inputs procurement and sales of outputs. Our FGDs in 2018 field visits to a few clusters identified several cases where the enterprises shared large machines. Boilers, generators, CNC (computer numerical control) machines, etc. were shared by a number of enterprises of clusters in light engineering clusters. In addition to this, we also found enterprises sharing transports with others in the same cluster. This sharing was found to be prominent in the garments cluster in the Nilphamari district. The major raw material of this garment cluster is the unused garment waste (locally known as "jhoot") of the large garment industries in Dhaka, Gazipur, and Narayanganj districts. The enterprises of the garment cluster in the Nilphamari district reported that they cut down transportation costs by a significant margin by pooling shipments. Our pre-survey FGDs found the incidence of sharing of labour with other firms in clusters – skilled workers in a few trades were occasionally required, such as technicians for repair works, and the costs for hiring these workers were found to be shared. Enterprises also reported informal sharing of labour based on mutual relationships.

Table 8.1: Marshallian Externalities: Sharing

Variable	Full Sample	Cluster SMEs	Non-Cluster SMEs	Mean Difference (p-value)
Share machine with other firms (% of firms)	0.186 (0.017)	0.18 (0.02)	0.162 (0.02)	0.0909
Share labour with other firms (% of firms)	0.026 (0.007)	0.04 (0.012)	0.012 (0.00)	0.0493
Share transport with other firms (% of firms)	0.092 (0.01)	0.152 (0.02)	0.032 (0.01)	0.0000
Share intermediate raw materials with other firms (% of firms)	0.014 (0.005)	0.012 (0.006)	0.016 (0.007)	0.7042

Note: Figures in parentheses are standard deviations.

Our survey asked if the firm shared machines, labour, transport, and raw materials. Table 8.1 shows that about 18 per cent of the cluster SMEs and 16 per cent of the non-cluster SMEs shared machines with other firms, and this difference is statistically significant at 10 per cent. In the case of labour, 4 per cent of the cluster SMEs and 1.2 per cent of the non-cluster SMEs shared labour. There is a significant difference between cluster and non-cluster in the case of transport sharing – about 15 per cent of the cluster SMEs shared transport with neighbouring SMEs, and this figure is only 3.2 per cent for non-cluster firms. The share of SMEs sharing raw materials is meagre – 1.2 per cent for cluster and 1.6 for non-cluster firms.

8.2 Matching

Producers and suppliers (raw materials, workers) tend to locate closer to each other to reduce search costs. Firms can also reduce transaction costs when locating near both customers and suppliers. It is argued that in a cluster, the number of job seekers and vacancies are in equilibrium quicker than in a non-cluster area (Duranton & Puga, 2004).

Table 8.2: Marshallian Externalities: Matching

Variable	Full Sample	Cluster SME	Non-Cluster SME	Mean Difference (p-value)
Number of days taken to find labour	4.20 (0.15)	4.09 (0.21)	4.31 (0.21)	0.4737
Number of days taken to find non-labour inputs	2.35 (0.05)	2.30 (0.07)	2.40 (0.08)	0.3502

Note: Figures in parentheses are standard deviations.

In this case, we asked about the number of days taken to find labour and non-labour inputs. Table 8.2 shows that for labour and non-labour, non-cluster SMEs took longer to find inputs, though the difference is not statistically significant. Cluster SMEs took about 4.09 days to find labour, whereas non-cluster SMEs took 4.32 days. For non-labour inputs, the corresponding figures are 2.3 days and 2.4 days. In short, we did not find any statistically significant differences in matching labour and non-labour inputs between clustered and non-clustered SMEs.

8.3 Learning

Agglomeration facilitates knowledge spillovers. An exchange of knowledge creates positive externalities for the firms and increases the productivity of the firms. We examined three types of learning related to technology, business, and skills and asked if the SMEs had learned anything from each other. We found that a significantly higher share of clustered SMEs reported that they learned business and skill-related knowledge from other SMEs more than the non-clustered ones (Table 8.3). About 62 per cent of clustered SMEs and 50 per cent of non-cluster SMEs learned business-related knowledge from other SMEs. In the case of learning skill-related knowledge, the share of clustered SMEs is 59 per cent, and the share of non-cluster SMEs is 41 per cent. There is no statistically significant difference between these two groups regarding technology-related knowledge.

Table 8.3: Marshallian Externalities: Learning

Variable	Full Sample	Cluster SME	Non-Cluster SME	Mean Difference (p-value)
Technological knowledge	0.246	0.264	0.228	0.3510
	(0.01)	(0.02)	(0.02)	
Business related knowledge	0.556	0.616	0.496	0.0069
	(0.02)	(0.03)	(0.03)	
Skill related knowledge	0.502	0.592	0.412	0.0001
	(0.02)	(0.03)	(0.03)	

Note: Figures in parentheses are standard deviations.

8.4 Implications for Resilience during COVID-19

The agglomeration forces of sharing, matching, and learning externalities can also contribute to improving the resilience of SMEs in clusters. We found evidence that physical proximity enhances both market and non-market interactions in the case of sharing and learning. In essence, we observe greater sharing of workers and transportation and business and skill-related learning from each other in the clusters than the SMEs outside clusters. This sharing and learning might have led to greater access to formal and informal credits, aids, and alternative employment opportunities in times of crisis.

As argued before, clustered SMEs might have greater and more accurate information on the government's bailout packages. When we conducted the second round of telephone surveys, the bailout packages (i.e., subsidised credit) had already been announced. Table 8.4 shows that almost all SMEs in clusters (about 99 per cent) were aware of the government incentive packages in the month of May during the first round of surveys in 2020. About 93 per cent of non-clustered SMEs knew about the package. Note that the first package for the cottage, micro, small, and medium enterprises worth BDT 200 billion was announced on 5 April 2020. In the last round, we asked how many of them received the subsidised credits announced by the government.[7] About 27 per cent of the clustered SMEs and about 19 per cent of the non-clustered SMEs received this credit.

[7] Entrepreneurs availed of the working capital loan/investment facility from the banks and financial institutions at a 9 per cent interest rate under the package, out of which 5 per cent interest was subsidised. This facility was effective from 13 April 2020 to 31 October 2020 but was extended up to 31 March 2021 for allowing banks and NBFIs sufficient time to disburse the working capital for the cottage, micro, small, and medium enterprises (Bangladesh Bank, 2021).

Table 8.4: Clusters vs. Non-clusters: Coping Strategies

	Sample Size (cluster, non-cluster)	Cluster	Non-Cluster	Differences (p-value)
Enterprise survey				
Knew about government incentive package (1st round)	350 (175,175)	173 (98.85)	162 (92.57)	0.084
Received subsidised govt. loan (3rd round)	345 (175,170)	48 (27.43)	33 (19.41)	0.073
Worker survey				
Received any financial aid from any sources (e.g., Govt., NGOs, etc.) (3rd round)	334 (170, 164)	69 (40.58)	65 (39.39)	0.891
Took any informal loan (e.g., money lender, friends)? (3rd round)	334 (170, 164)	71 (41.76)	60 (36.58)	0.221
Engaged in any alternative employment when the factory was closed. (3rd round)	334 (170, 164)	34 (20.00)	23 (14.02)	0.093

Note: Figures in parentheses in the second column are the sample size of clusters and non-clusters. Figures in other cells are percentages of the respective samples.

In the worker survey, we also asked if they received any financial help, took any informal loans, and opted for alternative employment when the factory closed. About 41 per cent of clustered SMEs and 39 per cent of non-clustered SMEs received any financial aid. However, in the case of loans, a larger number of workers in the clusters took informal loans from money lenders or friends (42 per cent vs. 37 per cent). Interestingly, a greater number of cluster workers were involved in alternative employment – 20 per cent for clusters and 14 per cent for non-clusters.

CHAPTER 9
CONCLUSION

Agglomeration forces have many benefits – they incentivise firms to locate close to each other so that inputs and outputs can be shared and matched with greater ease, both formally and informally. Information and knowledge sharing between firms has become critical for growth, and industrial clusters are argued to facilitate such sharing. The evidence of the benefits of such forces, as manifested in higher labour productivity, export growth, innovations, etc., is well grounded. In this study, we take this literature further and contribute to a very thin literature on agglomeration and resilience. We generate evidence that the SMEs in clusters were more resilient than the SMEs outside c

lusters in Bangladesh during the recent pandemic induced by COVID-19.

Using a pre-COVID survey of 2018 designed to study Marshallian externalities in the context of clustered and non-clustered SMEs, we conducted three rounds of follow-up surveys over the telephone from May 2020 to March 2021. We observe a sharp V-shape recovery of all the SMEs. However, the clustered SMEs registered stronger rebounds than the non-clustered SMEs, particularly towards the end periods of recovery. Relative to February 2020, the clustered SMEs' monthly production, sales, and inventories were significantly higher than non-clustered SMEs. In the case of employment, the recovery was driven by the higher employment of temporary workers. Additionally, the share of the workers who returned to the village is higher for the non-clustered SMEs.

To the best of our knowledge, this is the first evidence of the association between agglomeration and resilience in a developing country context. Many developing countries have been pursuing cluster-based SME development strategies to exploit the agglomeration forces for higher productivity. Our findings add one more justification for such strategies – clustering can also be effective in managing shocks.

REFERENCES

Asian Development Bank. (2012). The informal sector and informal employment in Bangladesh, *Country Report 2010*, Manila, Philippines.

Audretsch, D. B., & Feldman, M. P. (1996). R & D spillovers and the geography of innovation and production. *The American Economic Review*, *86*(3), 630-640.

Bangladesh Bank. (2021). Covid-19 pandemic in Bangladesh: Policy responses and its impact, Special Publication.

Bangladesh Bank. (2021). Covid-19 pandemic in Bangladesh: Policy responses and its impact. *SAARC FINANCE Cell, Research Department, Bangladesh Bank. Retrieved December 10*, 2022.

Behrens, K., Boualam, B., & Martin, J. (2020). Are clusters resilient? Evidence from Canadian textile industries. *Journal of Economic Geography*, *20*(1), 1-36.

Bakht, Z. (2021). Development of the MSME sector in processing and manufacturing. *Background Papers for 8th Five Year Plan*, *2,* Planning Commission, Government of Bangladesh.

Ciccone, A., & Hall, R. E. (1996). Productivity and the density of economic activity. *American Economic Review, 86* (1), 54-70.

Cirera, X., Cruz, M., Grover, A., Iacovone, L., Medvedev, D., Pereira-Lopez, M., & Reyes, S. (2021). Firm recovery during COVID-19: Six stylized facts. *Policy Research Working Paper, 9810*. World Bank, Washington, DC.

Dandekar, A., & Ghai, R. (2020). Migration and reverse migration in the age of COVID-19. *Economic and Political Weekly*, *55*(19), 28-31.

Delgado, M., Porter, M. E., & Stern, S. (2016). Defining clusters of related industries. *Journal of Economic Geography*, *16*(1), 1-38.

Duranton, G., & Puga, D. (2004). Micro-foundations of urban agglomeration economies. *Handbook of Regional and Urban Economics*, *4*: 2063-2117. Elsevier.

Duranton, Gilles, Martin, P., Mayer, T., & Mayneris, F. (2010). The economics of clusters: Evidence from France. *Oxford: Oxford University Press.*

Ellison, G., Glaeser, E. L., & Kerr, W. R. (2010). What causes industry agglomeration? Evidence from coagglomeration patterns. *American Economic Review*, *100*(3), 1195-1213.

Ellis-Petersen, H., & Ahmed, R. (2020). Bangladesh garment factories reopen despite coronavirus threat to workers. *The Guardian*.

Fairlie, R. W. (2020). *The impact of Covid-19 on small business owners: Evidence of early-stage losses from the April 2020 current population survey* (No. w27309). National Bureau of Economic Research.

Fujita, M., & Thisse, J. F. (1996). Economics of agglomeration. *Journal of the Japanese and International Economies*, *10*(4), 339-378.

Guerrero-Amezaga, M. E., Humphries, J. E., Neilson, C. A., Shimberg, N., & Ulyssea, G. (2022). Small firms and the pandemic: Evidence from Latin America. *Journal of Development Economics*, *155*, 102775.

Harris, J. (2014). The messy reality of agglomeration economies in urban informality: Evidence from Nairobi's handicraft industry. *World Development*, *61*, 102-113.

Howland, D. (2020). COVID-19 wreaks havoc on inventories. *Retail Dive.*

Iqbal, K., Munshi, F., & Andalib, S. (2012). Small and Micro Enterprise (SME) development in Bangladesh. *Sixth five year plan of Bangladesh 2011-15 background Papers*, *4*, Bangladesh Institute of Development Studies and Planning Commission of Bangladesh.

Kantor, S., & Whalley, A. (2014). Knowledge spillovers from research universities: Evidence from endowment value shocks. *Review of Economics and Statistics*, *96*(1), 171-188.

Kantor, S., & Whalley, A. (2019). Research proximity and productivity: Long-term evidence from agriculture. *Journal of Political Economy*, *127*(2), 819-854.

Krugman, P. (1991). Increasing returns and economic geography. *Journal of Political Economy*, *99*(3), 483-499.

Lall, S. V., Shalizi, Z., & Deichmann, U. (2004). Agglomeration economies and productivity in Indian industry. *Journal of Development Economics*, *73*(2), 643-673.

Martin, P., Mayer, T., & Mayneris, F. (2017). Are clusters more resilient in crises? Evidence from French exporters in 2008-2009 in the in The Factory-Free Economy: Outsourcing, Servitization, and the Future of Industry, Lionel Fontagné, Ann Harrison (ed.), Oxford University Press.

Martin, R. (2012). Regional economic resilience, hysteresis and recessionary shocks. *Journal of Economic Geography*, *12*(1), 1-32.

Martin, R., & Sunley, P. (2015). On the notion of regional economic resilience: Conceptualization and explanation. *Journal of Economic Geography*, *15*(1), 1-42.

Moretti, E. (2021). The effect of high-tech clusters on the productivity of top inventors. *American Economic Review*, *111*(10), 3328-3375.

Nordhagen, S., Igbeka, U., Rowlands, H., Shine, R. S., Heneghan, E., & Tench, J. (2021). COVID-19 and small enterprises in the food supply chain: Early impacts and implications for longer-term food system resilience in low-and middle-income countries. *World Development*, *141*, 105405.

Ruan, J., & Zhang, X. (2009). Finance and cluster-based industrial development in China. *Economic Development and Cultural Change*, *58*(1), 143-164.

Saxenian, A. (1994). Regional advantage: Culture and competition in Silicon Valley and Route 128, Cambridge, MA: Harvard University Press.

Sonobe, T., & Otsuka, K. (2011). Cluster-based industrial development: A comparative study of Asia and Africa. Springer. New York: Palgrave Macmillan, 2011

SME Foundation, (2013). SME clusters in Bangladesh. SME Foundation, Bangladesh.

Visser, E. J. (1999). A comparison of clustered and dispersed firms in the small-scale clothing industry of Lima. *World Development*, *27*(9), 1553-1570.

World Bank (2022). *Bangladesh development update: Recovery and resilience amid global uncertainty*. Washington DC.

APPENDIX

Table A1: Distribution of Samples for SME Clusters

Cluster	District	Sub-districts	Pre-COVID-19 Sample Size*	Regression Sample	
				Clustered SMEs	Non-Clustered SMEs
Leather	Kishoreganj	Bhairab	44	30	30
Clothing	Tangail	Delduar	35	25	24
Sari (Jamdani)	Narayanganj	Rupganj	25	17	17
Plastic	Dhaka	Chakbazar	25	17	17
Hosiery	Pabna	Pabna Sadar	20	14	14
Light Engineering	Dhaka	Sutrapur	15	10	10
Garments	Nilphamari	Syedpur	15	10	8
Rice Mill	Kushtia	Kustia Sadar	10	7	7
Light Engineering	Bogra	Bogra Sadar	10	7	7
Electrical Goods	Dhaka	Jatrabari	10	7	7
Leather	Chittagong	Chittagong city corporation	10	7	7
Home Textile	Bogra	Adamdighi	10	7	7
Perfume/ incense	Moulvi Bazar	Borolekha	7	5	5
Cricket Bat	Pirojpur	Nesarabad	7	5	5
Embroidered quilt	Jamalpur	Sadar	7	5	5
	Total		250	174	170

Note: *The sample size of the cluster and non-cluster SMEs are the same. Note that 5 observations from non-clustered SMEs and 1 observation from clustered SMEs are dropped in our regression sample due to missing observations.

Table A2: Comparison of Pre-Covid Characteristics of the Full Sample and Our Sample

Variables	Full Sample			Clustered Sample			Non-clustered Sample		
	Full (500)	Our Sample (350)	Mean diff. (p-value)	Full (250)	Our Sample (175)	Mean diff. (p-value)	Full (250)	Our Sample (175)	Mean diff. (p-value)
Total employment	17.1	19.57	-2.47	17.8	21.47	-3.67	16.4	17.83	-1.43
	(42.6)	(50.29)	(0.45)	(42.1)	(47.67)	(0.24)	(33.3)	(36.88)	(0.68)
Total output (BDT 100,000)	64.9	73.77	-8.87	75.6	81.22	-5.62	54.3	60.22	-5.92
	(168.43)	(159.04)	(0.43)	(187.22)	(199.16)	(0.68)	(164.99)	(179.50)	(0.73)
Total sales (BDT 100,000)	60.2	68.83	-8.63	70.3	72.89	-2.59	50.1	54.81	-4.71
	(173.82)	(184.08)	(0.50)	(196.48)	(198.29)	(0.82)	(173.91)	(181.29)	(0.77)
Capital stock (BDT 100,000)	7.03	8.12	-1.09	9.01	11.34	-2.33	5.05	6.66	-1.61
	(13.77)	(14.27)	(0.27)	(20.35)	(23.56)	(0.13)	(11.74)	(13.32)	(0.19)
Output-labour ratio (BDT 100000 per labor)	3.8	3.77	0.03	4.25	3.78	0.47	3.31	3.38	-0.07
	(5.2)	(4.9)	(0.93)	(6.42)	(5.39)	(0.46)	(4.36)	(4.11)	(0.88)
Capital-labour ratio (BDT 100,000 per labour)	0.41	0.42	-0.01	0.51	0.53	-0.02	0.31	0.37	-0.06
	(0.74)	(0.83)	(0.86)	(0.92)	(1.21)	(0.79)	(2.2)	(2.8)	(0.81)

Note: Figures in parentheses are standard deviations.

Bangladesh Institute of Development Studies
E-17, Agargaon, Sher-e-Bangla Nagar, Dhaka-1207, Bangladesh
Tel: 88 02 58160430-37, Email: info@bids.org.bd, Web: www.bids.org.bd