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IZA DP No. 17106

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ABSTRACT

Employment Booms and Infant Health: Evidence from the Ready-Made Garment Sector in Bangladesh

In this paper, I estimate the inter-generational health impact of maternal employment opportunities using evidence from the ready-made garment industry in Bangladesh. This industry was exposed to a trade liberalization policy in 2005, which generated spatial and temporal variation in the establishment of garment factories and therefore, potential employment opportunities for women. Using a difference-in-difference strategy, I find that the expansion of this sector improved the probability of neonatal survival for children who are born in areas that experience higher growth in employment opportunities post trade liberalization. This is driven by the improved labor market participation by mothers, enabling them to delay childbirth and improve their intra-household bargaining power.

JEL Classification: J21, I15, I12

Keywords: neonatal mortality, female labor force participation, ready-made garment sector

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1 Introduction

Over the last fifty years, there has been an increase in the number of women employed in low-skill manufacturing jobs in developing countries (Mammen and Paxson, 2000). Such participation in the labor force not only facilitates women's investment in education, leading to delayed marriage and childbirth (Heath and Mobarak, 2015), but these developments in women's lives may hold considerable implications for the well-being of their future generations. While improved maternal health and knowledge from delayed childbirth may benefit child health, the time spent at work, especially just before and after childbirth, may limit the time spent for childcare, potentially crowding out the positive effects on child health.

In this paper, I assess the impact of an expected increase in maternal employment opportunities on child health using evidence from the ready-made garment (RMG) sector in Bangladesh. Over the past two decades, there has been a significant rise in the number of employed women in Bangladesh. Compared to other South Asian nations, Bangladesh stands out as a prime example of fostering female job growth, particularly due to its thriving RMG sector. Until 2004, the RMG sector in Bangladesh was restricted by the Multi Fibre Agreement, which controlled global trade in textiles and garments, imposing quotas on developing countries and granting export rights to only select firms. This agreement lapsed on January 1, 2005, increasing the total employment in this sector by over 1 million, and an increase in women's employment in both existing and newly established factories (Rahman and Siddiqui, 2015). Using administrative data from the biggest trade union in the country, I show in Figure 1 that the employment increased immediately after the policy change, and newer factories were set up a few years later. Ahmed et al. (2014) show that indeed after the removal of these quotas, there are a significant increase in textile exports right after 2005[1].

I leverage rich nationally representative surveys and administrative data on RMG factory location to exploit spatial and temporal variation in employment opportunities resulting from this trade reform. I use the distribution of the number of factories close to women's homes before the trade shock to identify areas with significant and minimal potential for employment growth as the high density (treated) and low density (control) groups, respectively, using a pre-defined cut-off number of factories[2]. Using a

[1] Using data from the World Trade Organization, the authors show in Figure 1 in their paper that there is an increase in exports in Textile exports, Clothing exports and Merchandise exports data over time.

[2] I show in Figure B1 that the treated or the high density areas had a larger growth in the number of factories after

difference-in-difference model within an intent-to-treat framework, I estimate the impact of maternal job opportunities on the probability of child's survival by comparing outcomes for children born in treated versus control areas before and after the lapse of the policy. In my analysis, I exclusively focus on areas that have a ready-made garment factory in the two main garment producing and populous divisions in Bangladesh - Dhaka and Chittagong.

I find that the increased exposure to jobs significantly improves the chances of a child survival in their infancy, specifically within one month of their birth. This effect is strongest for the years immediately following the announcement of the policy. I argue that this reduction in neonatal mortality may be driven by a combination of factors. First, I find that there is an increased female labor force participation, especially after their childcare needs are met, leading to improved management of the trade-off between labor market participation and childcare in response to the higher availability of jobs for women. Second, there might be greater contributions to household income by women exposed to these employment opportunities, as measured by women's improved bargaining power within the household. Third, I find an increase in the childbearing age of women, and these improvements in fertility outcomes could lead to improvements in neonatal survival of their children. I do not find any impact on the differential access to health care by women, employment status of men or any changes to the household's stock of assets, that may have impacted the survival of children in their neonatal age favorably.

In Bangladesh, policies such as paid maternity leave[3], childcare facilities including crèches [4], and regular family planning programs can influence mothers' health investment behavior[5]. Despite the physically demanding nature of work in garment factories, access to formal sector jobs and leave provisions may allow women to invest in childcare during the child's crucial age. While the survey data does not allow me to observe the time spent by women in labor market and in healthcare related tasks around child-birth, the outcomes I study are closely linked to maternal behavior around childbirth and care during

the policy change, while the low density areas did not grow as much.

[3]The 2006 Labor Law in Bangladesh grants employer-sponsored paid maternity leave for 16 weeks to women.

[4]Chapter 5, Section 47 of Factories Act, 1965 makes it mandatory for factories in Bangladesh with more than 50 workers to have separate rooms for children, under the age of 6 years, of mothers working in the factory. This is, however, seen by factories as mere compliance, and quality childcare is absent (UNICEF, 2015)

[5]The legal standards for formal leaves are, however, not observed in practice. Often women either take shorter leaves, unpaid leaves, or do not return to the same factory after investing their time in child-care at the time of birth (UNICEF, 2015). In such contexts where maternity leave policies are absent or underutilized, the trade-off between time spent on work or on health inputs can become even more costly. Nevertheless, the availability of formal sector jobs and leave provisions may enable women to take unpaid maternity leaves or temporarily leave their jobs to provide better care for their children.

the vulnerable neonatal period. This is supported by the findings in this paper, particularly concerning short-term health outcomes like the child's survival in the neonatal age. Further, using the subsample of women based on the age of their children, I provide suggestive evidence that women are able to go back to the labor market when their childcare needs are met.

The validity of the difference-in-difference approach requires that in the absence of the policy, child health in the treated and control groups will evolve similarly. I provide empirical evidence supporting this parallel trends assumption and show the sensitivity of these results to a possible violation of the parallel trends assumption using the methodology developed by Rambachan and Roth (2023). I show that these results are robust to treatment effect heterogeneity using the imputation method developed by Borusyak et al. (2021). While this lack of pre-trends in the child-health outcomes is a necessary condition but not a sufficient condition to establish the validity of this research design, I combine this analysis with other suggestive and descriptive checks to rule out factors that could change across clusters over time, that could lead to changes in mortality outcomes and labor market opportunities, and show the robustness of the main results. I rule out the potential role of compositional changes of the women in the high density clusters after the reform by looking at selective migration of mothers with better education, skills, and knowledge about childcare into the areas with more jobs. Further, I show that access to healthcare infrastructure and information, as a proxy for changing road networks or access to other public programs, remains stable over time. I also show that the results are robust to varying definitions of the treatment and control group.

This paper contributes to the growing literature on the relationship between women's employment opportunities and infant health in low and middle income countries, by focusing on a context where there are accessible year-round semi-skilled jobs that have institutionalized child care for women. The key concern in increasing women's labor force participation in most developing countries with precarious jobs for women is the trade-off they face between the time spent in meeting work-related demands or on health inputs around child birth, that could impact the health of newborns. Recent evidence from such countries suggests that maternal employment, particularly in physically demanding workfare or seasonal jobs with high work-related demands, can lead to a decline in newborn survival rates (Chari et al., 2019; Miller and Urdinola, 2010; Bhalotra, 2010). This is due to the time-intensive nature of childcare and the lack of suitable substitutes for maternal care. Most of these studies, however, focus on seasonal economic shocks in rural areas.

Research focusing on permanent shocks to urban households due to trade liberalization, has found mixed evidence, both in terms of the direction of the effect and the mechanisms driving the relationship. A permanent increase in labor market opportunities for women may impact children's health through higher income, increased intra-household bargaining power, or improved environmental conditions (Panda, 2020; Atkin, 2009; Majlesi, 2012; Benshaul-Tolonen, 2018). Conversely, there is also empirical evidence on improving employment opportunities for women being bad for child health. Charris et al. (2023) and Karim (2023) find that worsening female labor market employment reduces child mortality due to a greater focus on time-intensive health inputs and selective fertility. Thus, while maternal employment can boost household income, it may only partially offset the negative effects on child health.

In a closely related paper, Heath and Mobarak (2015) study the impact of the access to these RMG factories on women's employment, education outcomes and childbearing decisions. The empirical strategy adopted in this paper, however, differs in two ways: First, they conduct a primary survey and compare girls who live close to the garment factories with those who live further away, with boys as their control group. Instead, I compare women and their children who live in areas that have very high density of RMG factories, with the women and their children who live in areas with low density of RMG factories. Second, I look at all the factory regions in Dhaka and Chittagong in Bangladesh, while their data is collected in selected peri-urban areas outside of Dhaka city. The employment and fertility results found in this paper are similar to their findings, and I extend their work by looking at intergenerational outcomes using a more generalized sample. These results emphasize the impact of jobs with amenities such as childcare facilities and maternity leave on child health, highlighting the policy relevance of such provisions for women's employment in public work programs and labor market.

The next section discusses the setting of the ready-made garment sector in Bangladesh and the trade liberalization policy that I exploit for my analysis. Section 3 has details on data sources and the empirical strategy. In Section 4, I discuss the results and mechanisms. I conclude with a discussion on the policy implications of these results for maternal employment opportunities.

2 The Ready-Made Garment Sector in Bangladesh

The garment export industry in Bangladesh started in the late 1970s. It has experienced tremendous growth over the last 30 years, and Bangladesh has now become a top global exporter of garments. In 1984, there were almost 400 factories employing 120,000 workers; since then, the industry has expanded and currently, there are over 4000 factories employing about 4 million workers (from a total workforce of almost 74 million). As of 2010, the country had an overall USD 15 billion in export value, and the RMG sector made up 13 percent share of GDP and a total export value of over 75 percent (McKinsey and Company, 2011). The US and European Union are the two largest markets for Bangladesh's apparel. Cheap labor and capacity have been identified as the two main factors in making the country an apparel-sourcing hot spot for international buyers.

The industry was governed under the Multi Fibre Agreement (MFA) since 1974. This was an international trade agreement on textiles and clothing, which imposed quotas on the amount of clothing and textile exports from developing countries to developed countries. The intent of this agreement was to protect the domestic producers and garment industry in the importing country. In the Uruguay Round negotiations in January 1995, under the World Trade Organization (WTO) Agreement on Textiles and Clothing (ATC), the MFA was made defunct. It was decided that the quotas under MFA would be gradually phased out over the 10-year period of 1995-2005. The end of these textile and clothing quotas allowed for trade to be regulated by the normal WTO rules. All WTO members now had unrestricted access to the US, EU, and Canadian markets. Bangladesh benefited from the removal of these quotas in only the last phase of the removal of the agreement in January 2005 [6].

The number of factories in RMG industries rose further, and there was even a jump in the total employment in the industry. Using the aggregate official statistics published yearly by the Bangladesh Garment Manufacturers and Export Association (BGMEA), in Figure 1, I show the growth in the number of factories and employment over time in the country. There is an evident jump in the number of employees after 2005, from 2 million to over 3 million. There is a change in the number of factories

[6] The restrictiveness of these quotas was different for individual exporting countries. Therefore, the removal of quotas affected the export competitiveness of each country differently. Bangladesh has lower wages compared to most of its competitors. Despite that, due to the low productivity of its labor force coupled with inadequate infrastructure and intense competition from China, it was speculated that the Bangladeshi exporters would not be able to compete in the short to medium term and that exports would actually fall after the removal of quotas (Yang and Mlachila, 2007). The trade from the textile sector, however, flourished after 2004 (Rahman et al., 2008).

as well, but that kink is observed a year later which is expected, due to the gestation period in setting up new factories. Moreover, Ahmed et al. (2014) show that indeed there was an increase in the export volume from Bangladesh after the removal of the MFA quotas. The authors use data from the World Trade Organization[7] to show that since 2005, clothing exports grew at an average annual rate of 25%, and a sharp increase in observed right after 2005 in textile exports.

According to the BGMEA, out of the roughly 4 million employees working in the RMG sector, 80 percent are young women, and most of them are rural migrants from poorer sections of the rural population. Other sources from the Bangladesh Bureau of Statistics and the Bangladesh Labor Force Survey suggest the share is between 50-60 percent. Nevertheless, women make up a considerable share of the Bangladeshi RMG sector with a varying share of female employment depending on the production sector (Matsuura et al., 2020).

Rahman et al. (2008) cite evidence which suggests that the RMG sector is economically more suitable for women than men; wages of unskilled male labor in the countryside are higher than the wages earned by unskilled male labor in RMG factory. On the other hand, women typically earn more than double the wage in a RMG factory as compared to other unskilled work (Sobhan and Khundker, 2001). However, there are systematic gender inequalities in wages earned in the garment industry (Paul-Majumder and Begum, 2000; Menzel and Woodruff, 2019). Kabeer and Mahmud (2004) in their survey attempted a more systematic comparison of wages and working conditions of women in these factories and find a lot of variation in the nature of working conditions across factories. They found that the women working in factories in the Export Processing Zones (EPZ) were more educated and had a more "formal" employment contract with their employers. They tended to have access to on-site training and were allowed to avail a variety of benefits that come with a formal sector job - such as childcare leave, paid leave, and medical facilities. These women were earning much higher wages as compared to other forms of urban employment. The factories that are situated outside the EPZs operate in a much more "informal" setting, with lower wages, longer hours, at times paid wages in kind, and poorer working conditions. Despite this, the women working in these factories were more financially secure as compared to other female wage workers in the urban economy. Expansion of the ready-made garment industry, could provide women with the opportunity to work in jobs close to their homes, instead of either being

[7] Refer to Figure 1 and the discussion in Section 2 about the Ready-Made Garments Sector in Bangladesh in their paper.

unemployed or working in seasonal and maybe even precarious jobs. Access to these jobs could allow women to have a regular income, and with that the possibility of changing their childbearing decisions and an improved agency within the household.

3 Data

I construct a unique record of births exposed to the RMG factories using the spatial distribution of RMG factories in Bangladesh to measure an individual woman's (thereby her children's) exposure to enhanced employment opportunities on account of proximity to factories. These data are combined with the 5-year retrospective birth history data from individual women surveyed by the Demographic and Health Survey (DHS) in Bangladesh in the years 1999, 2004, 2007, and 2011.

3.1 Factory data

The Bangladesh Garment Manufacturers and Export Association (BGMEA) is a recognized trade body that represents export-oriented garment manufacturers and garment exporters in the country. I use the list of factories enrolled as members of the BGMEA. This union has all woven garment factories and 90 percent of the knitwear factories are registered with them. Apart from establishing and promoting contacts with foreign buyers, businesses, and trade associations, the union sends members to apparel fairs. It also co-sponsors welfare programs for garment workers in areas of healthcare, transportation, social security and insurance coverage, housing, and skill training. The factories pay dues of 470-570 USD to BGMEA based on the number of machines they own, as a membership fee.

The BGMEA website[8] provides information on the name, address, year of establishment, total number of current employees, and production capacity of each of these members. I scraped this list in May 2019 and geocoded these addresses to determine their spatial location. The trade union at the time of webscraping had 4370 members, and I precisely geocode approximately 92% of the firms.[9]

[8] http://www.bgmea.com.bd/member/memberlist

[9] More details about the webscraping and the missing factories are in Appendix B.

3.2 DHS data

The Bangladesh DHS is a nationally representative survey of ever-married women in the age group of 10-49 years. The survey provides rich data on the composition of households, education, health, fertility, and economic participation of women. As per the survey conducted by Matsuura et al. (2020), around three-quarters of women in the RMG factories are married women, making the DHS survey a reliable source of data to use. In each wave of the survey, the data are collected for all 6 divisions and 64 districts in Bangladesh. Each year, a sample of around 10,000 households is chosen from a total of 300-400 clusters. A cluster is a sampling unit defined by the DHS survey. It is either a village or a group of villages. Each cluster has an average of 26 households, ranging from 8 to 68 households. Each year of the survey, however, does not necessarily include the same set of clusters within a district. Along with these modules, I use restricted-access spatial data, which gives the latitude and longitude of the centroid of each cluster.[10]

The survey includes a birth history module on the children born to these women in the last 5 years from the survey. This module has extensive information on the birth and death details of these children and the health investment in terms of breastfeeding, vaccination, nutritional inputs, and pre-natal care by the mother for each of her children. It also records the height and weight of the children, which I utilize to calculate height-for-age, weight-for-age, and height-for-weight Z scores. I use these indicators to measure infant health. A sample of these women's husbands is also selected for information on their education, fertility preference, and their household participation.

For mother-specific outcomes like employment and fertility, I use the woman's record rather than the child's. The child record is only for women who gave birth in the 5 years prior to the survey. In order to measure the response of women to employment opportunities, it is more viable to include all ever-married women, including those who have had no new child in the last 5 years. The women who never had children are not included in the fertility analysis. Table 1 shows the summary statistics of the variables considered in the analysis.

[10] I cannot observe individual households' locations. For confidentiality reasons, these GPS coordinates are displaced up to 2 km in urban areas and 5 km in rural areas, with 1% of rural locations displaced up to 10 km.

3.3 Defining Treatment and Control Group

To define an individual's exposure to RMG factories, I take each cluster in each year as the centroid and define a 10 km buffer area around this coordinate. I assume this encompasses the commuting range for individuals. I use the number of factories within the catchment area of clusters to define the treatment and control groups by evaluating whether the clusters have a low density of factories or a high density.

Ideally, I would use the same clusters within a district over time to look at how high-density clusters fared over time in comparison to the low-density. In the absence of these data, I count the number of factories in the catchment area of all clusters in the pre-reform period (i.e., in 2004) and classify each cluster as low density or high density based on a cut-off. This cut-off is chosen as 50 factories, which is roughly the 35th percentile of the factory distribution.[11] Figure 2 shows an example of how individual exposure is defined.

Using the distribution of the number of factories in the high and low-density clusters, before and after the reform, as shown in B1, I show that the low-density clusters experience lower growth in the number of factories over time; whereas the high-density clusters experience massive growth in the number of factories that are added in that region post-2005. The average increase in the number of factories in low-density areas is 0.25 from 2004 to 2007 (the range being 0 to 13); and 0.43 from 2007 to 2011 (the range being 0 to 31). In the high-density clusters, the average increase in the number of factories is 48.14 from 2004 to 2007 (with the range of 10 to 135); and 55.92 from 2007 to 2011 (range of 9 to 195).

Additionally, I check the sensitivity of my results by using 15 Km buffer areas instead of 10 Km, and also by varying the definition of high density to other values between 30-80 in intervals of 10 factories.

3.4 Measurement Error

There are two possible sources of measurement errors in defining an individual's exposure. First, the factories that I did not manage to geocode, could be large factories, or concentrated in specific areas. In Appendix Table A1, I compare the number of management employees (the data on other employees is mostly missing), number of machines, and the yearly production capacity (in dozens) of the factories that I managed to geocode and those that I could not geocode. While the median values are comparable,

[11] My estimates would be attenuated if the individuals surveyed in 2007 and 2011 in the low-density regions also get affected by the trade shock.

the mean values of these indicators for the non-geocoded factories are almost half of that of the geocoded factories. Therefore, the factories that I did not manage to geocode are in fact on an average smaller factory than the ones geocoded. The non-geocoded factories are located in districts that have a large number of factories - most of which are geocoded. Thus, it is safe to assume that this is not a large measurement error.

Second, I observe factories enrolled in BGMEA after the *Rana Plaza* factory disaster in 2013 that lead to a shutdown of factories that did not meet certain safety requirements. My analysis will suffer from a selection bias if I only observe the good quality factories in my data, and factories were shut down non-uniformly[12]. If the factories were shut down uniformly across all neighborhoods and all years, then this bias would be minimized. If most of the factories were shut down in areas that I categorize as low-density, my effects will be attenuated. To check the extent of this measurement error, Siddiqui (2022) compares the list of factories enrolled with BGMEA web scraped in 2021 with the actual directory of factories enrolled with BGMEA in 2000 and 2009. He finds that 71 percent and 80 percent of the web scraped list match with the directory in 2000 and 2009 respectively, suggesting a strong correlation between the spatial distribution of factories as seen now, and what it looked like before the *Rana Plaza* factory disaster, even though the number of factories might have reduced now.

3.5 Sample Restriction

I restrict to only those areas that produce readymade garments for this analysis. I include the clusters that get a factory between 1999-2011 and only look at two divisions, Dhaka and Chittagong, which have about 98.28% of the factories in my sample. These are the two most populous cities in Bangladesh and make up for roughly 8% of the population of the country. I have a total of 19 districts in my sample. For employment, I restrict my sample to individuals who are in the age group 18-40 since they are the ones who are most likely to be impacted by this policy change. I have a resulting sample size of 6257 women. Out of these, 626 women have no children. For my child health analysis, I have a sample size of 4131 children.

[12]Based on a survey of over 990 garment workers in peri-urban area outside Dhaka, Bangladesh, Heath et al. (2022) find that 47% of the factories in 2009 were not found in 2014.

4 Identification Strategy

The trade liberalization policy generated spatial and temporal variation in employment opportunities for women in the readymade garment sector in Bangladesh. I estimate an intent-to-treat effect of the expansion in employment opportunities for women who were likely to be exposed to the trade liberalization policy change in 2005, on their children's neonatal health. Since the factories are likely to be located in areas that are more developed, urban, or where women are more likely to be more educated, and more likely to be working, a simple comparison of employment and health outcomes in high-density and low-density areas may not capture the causal effect of the employment boom. To get at the causal effect, I only look at areas that get a factory at any point in time, since the baseline characteristics of such areas are speculated to be similar - i.e. good roads, better connectivity, etc[13].

Given that the health of children could be affected by several other outcomes of the employment booms, and not just maternal employment, I estimate the following baseline difference-in-differences (DID) regression specification:

$$Y_{ict} = \alpha + \beta_1.Post_t.High\_Density_c + \beta_2.High\_Density_c + \beta_3.Post_t + \gamma.X_{ct} + \rho.Z_{ict} + \tau_c + \eta_t + \epsilon_{ict} \quad (1)$$

where Y_{ict} is an indicator for neonatal mortality a child i born in cluster c in year t and takes the value 1 if the child dies within the first 1 month of birth, and 0 otherwise; $Post_t$ takes the value 1 if the birth year of the child is after the trade liberalization policy in 2005, and 0 otherwise; $High\_Density_c$ is a dummy that is defined for each cluster and takes the value 1 for treated clusters that were significantly exposed to the policy, and 0 for low density clusters or the control group that was relatively less exposed to the policy[14]. Since I do not observe the same clusters over time, I control for cluster-level variables that are relatively fixed over time and potentially unchanged by the treatment. These are included in

[13] This includes clusters in the sample that may have had 0 factories at the time of the survey, but eventually received a factory (as identified from the geo-coded factory locations).

[14] Clusters that had more than 50 factories in 2004 (before the trade liberalization policy) are categorized as high-density clusters, while the control group is clusters that had less than 50 factories in 2004. I check the robustness of the results by varying this threshold and show in Section 5.3 that the results are robust.

X_{ct}. Specifically, to control for geographical characteristics that may affect factory placement initially, I include the population density in 2005 which is the number of people (in 10,000s) residing per km in 2005 in the catchment area of each cluster; and the rainfall in 2005 that is measured as the millimeters (in 10,000s) of rainfall in 2005 in the catchment area of the cluster; and the fraction of households in a cluster that had access to piped water. Z_{ict} includes individual-level covariates and includes an indicator variable for whether the individual belongs to a rural or an urban household and the age of the mother[15]); τ_c are matched-cluster fixed effects. Since I do not have the same set of clusters over time, I match the clusters in 1999, 2007, and 2011 to their nearest cluster in 2004 using their locations and assign each cluster their 2004 cluster code for the cluster fixed effects using the methodology developed by Keskin et al. (2017). The analysis includes over 100 matched clusters. Since there could still be variation in clusters within these matched clusters over time, I control for cluster-level variables. Lastly η_t includes birth-cohort fixed effects. The parameter of interest is β_1, which represents the treatment effect of being exposed to the trade liberation policy. I cluster the standard errors at the cluster level.

4.1 Parallel Trends

The identifying assumption of this analysis is that in the absence of the policy, the probability of neonatal mortality in the high-density and low-density regions would have evolved similarly. I test for the parallel trends in neonatal mortality by constructing birth cohorts using the birth year of children from each of the survey years. This allows me to use 10 pre-periods to test for the parallel trends assumption. Figure 3(a) shows the unconditional mean of neonatal mortality in the high-density and low-density clusters over time. I do not find any visible divergence in the neonatal mortality in high and low-density clusters in the pre-periods. I formally check the conditional differences in neonatal mortality in the high and low-density clusters using an event study plot and as shown in Figure 3(b), there are no significant differences in the pre-periods[16]. Unfortunately, the event study analysis shows coefficients that might

[15] I also estimate my results by including an individual specific control on years of education of the women. Since education could potentially be impacted by the employment shock (Heath and Mobarak, 2015), I do not include it in the main specification. Given that I only have the set of married women, this variable can be seen as the completed education after which the woman gets married. My results remain unchanged.

[16] Note that to test for the mechanisms at the mother or the household level, I only use the DHS survey years since the data is only available at that level. To test for the parallel trends in these variables, I estimate the leads and lags of program effects and report the results in Table A3 and A4. The coefficients of interest are on the interaction term of high-density cluster and the year 2000. Except for birth spacing, I find the differences are not significantly different from zero.

be imprecisely estimated due to sample and noisy sample from the DHS recall data, as evident from the large confidence intervals. The direction of the result is interesting, nevertheless.

There is still a concern that even if there are no pre-existing differences in the trends in high and low-density clusters, the tests conducted above may fail to reject due to low power and the pre-treatment estimates are imprecise[17].To address this issue, I check the sensitivity of my analysis to possible violations of the parallel trends assumption and provide bounds using the approach by Rambachan and Roth (2023). I show in Figure A2 that the OLS estimates are robust to linear and non-linear parallel trend violations[18]

5 Results

I now present the empirical results. I begin by documenting a reduction in infant mortality, i.e. the probability of the child dying within the 1 year of their birth, of children who are born to mothers who were exposed to the employment boom. I then discuss the potential mechanisms behind these findings by discussing results on other mother and household-level characteristics.

5.1 Mortality

Table 2 shows the regression results for the probability of the death of a child in various age-groups. I show the results for survival of children in the first year of their birth (infant mortality), first month of their birth (neonatal mortality) and in the first five year of their birth (under-5 mortality).

The results indicate that with the removal of trade quotas and with the expansion of employment opportunities, there is an associated decrease in the probability of infant and under-5 mortality. This is driven by the improved rate of survival of children in their neonatal age, i.e. the first month of their birth. I find that there is no impact on children older than that, in the age groups 1 month - 5 years.

The reduction in probability of death of a child in their neonatal age is by 2.9 percentage points in

[17] Roth et al. (2023) discuss the latest literature on how this bias the estimates and the suggested methods to deal with this concern.

[18] The robustness is assessed for a range of values of M, where $M = 0$ is the scenario in which a linear trend in neonatal mortality is allowed to differ between the high and low-density clusters, and the higher values of M represent deviations from linearity in trends between the consecutive periods. I consider values of M ranging between 0 and 0.4. For the OLS estimates, the breakdown value is $M = 0.1$

the high-density regions. These effects are economically significant: the 2.9 percentage points reduction over the base of average probability of death of a child in their neonatal age of 4% is large.[19]

Given that the confidence intervals are wide, it is difficult to make a precise inference about the estimated effect size. Nevertheless, I benchmark the estimated effect against the literature. A close comparison to this paper is the study done by (Benshaul-Tolonen, 2018), in which they look at the impact of local industrial development or the setting up of gold mine on infant and neonatal mortality in Africa. While they look at industrial development broadly, they also find an increase in job opportunities for women as a result of this economic boom. The estimated effect size in their paper for neonatal mortality is very similar to what I find in the Bangladeshi context - with similar baseline neonatal mortality as well [20]. The estimated effect sizes on maternal employment booms on infant health in other contexts (e.g. Chari et al. (2019) in India and Miller and Urdinola (2010) in Columbia) are, however, smaller than what I find. It is worth noting that the Bangladeshi labor market context is different from the experiment discussed in the cited papers. The employment boom under consideration in Bangladesh is bringing semi-formal or formal sector jobs to women, as compared to an increase in informal or seasonal jobs in the cited papers. This difference in the estimate can also be attributed to the maternity leave of 16 weeks (or 4 months) offered to women working in the formal sector jobs in Bangladesh[21]. Even if the factory jobs under consideration do not comply with the workplace protection laws, these jobs allow women to take an unpaid or a temporary break from work and rejoin when their childcare needs are met, relieving the women from the difficult trade-off between income generating activities and time spent for childcare.

I next look at the effects on long-term health outcomes as measured by the weight and height of the surviving children. I look at the height-for-age, weight-for-age and wight-for-height Z-scores for these children. I show in Table A5 that such an employment boom has no impact on long-term health. Collectively, the impact on short-run health outcomes, and no impact on long-term mortality or health

[19]The dynamic effect of this policy can be seen in Figure 3(b). While we see a decline in neonatal mortality in the years close to the policy change, we see the effects becoming zero eventually, perhaps owing to the decline in neonatal mortality in low density regions. This could be driven by the overall reduction in neonatal mortality rates in Bangladesh over this time period. It is hard to disentangle the dynamic effects further.

[20]In Table 5, Benshaul-Tolonen (2018) finds that the mean neonatal mortality within one month of being born is 3.8% and the DID point estimate reduction is 2.8 percentage points.

[21]This sanctioned leave increased from 12 weeks to 16 weeks in the changes in Labor Law, 2006. However, the increase in maternity leave during this period is small and unlikely to cause the change in neonatal mortality and other mechanisms that I discuss further

outcomes suggests the key role of factors that might affect changes in behavior around the vulnerable stage of child birth.

5.1.1 Robustness

While there are no significant differences between the neonatal mortality trends in the pre-periods, the difference between the low and high-density clusters in the initial years is economically significant. A potential threat to identification would be if the factors that make high and low-density clusters inherently different from each other are causing differential changes in the low and high-density clusters over time. As shown in Table A2, in the pre-period, the observable characteristics of women, children, and households are different across the high and low-density regions. Given that the high-density clusters are more urbanized, while low-density clusters are more rural, there could be time-varying unobserved confounders that might invalidate the parallel trends assumption and impact neonatal mortality.

A possible confounder could be the migration of self-selected women with better childcare knowledge and ability into the high-density clusters after the policy change may be driving this effect. In the absence of migration information[22], I restrict the analysis to children who are born to women who got married before 2005. Given that most women migrants in developing countries migrate for marriage (Rosenzweig and Stark, 1989), this might be a proxy for migration. In fact for the women surveyed in 2007, 75% of the women who got married before 2005 have lived in their current residence since marriage. As shown in Table A7, I find that the magnitude of the estimated effects are robust to this subset as well.

Another threat could be the differences in access to healthcare infrastructure and information (e.g. women's health programs around factories, or self-selection of educated women in areas with better jobs, or better road networks leading to differential access to health care) that might be correlated with the treatment and therefore may bias the results. Using the cluster-level health and community amenities data, I check if the access to hospitals and healthcare centers is changing over time[23]. In my sample, the average time to travel to a hospital is stable over time, ranging between 79 minutes to 88

[22]The survey asks the women how long they have lived in their current place of residence for 1999, 2004, 2007, but not for 2011.

[23]Ideally, I would have liked to check for the change in access to healthcare in high and low-density clusters, before and after the policy change. However, the geolocation data for clusters in 1999 is not available, and I am unable to map the factory locations to those clusters

minutes.

Lastly, the results estimated by equation (1) could be biased if the treatment effects are heterogeneous across different groups or over time. Recent literature in econometrics has cautioned against the implicit assumption of homogeneous treatment effects estimated by a standard DiD regression like Equation 1. To ensure that the results are not biased, I check the robustness of these results to treatment effect heterogeneity using the imputation methods developed by Borusyak et al. (2021). As shown in Figure A1, I find that the OLS and Borusyak et al. (2021) estimates are very similar to each other. The estimates from this method are also robust to the linear and non-linear parallel trends violation as shown in Figure A2.

5.2 Mechanisms

An increasing amount of research has explored the link between maternal employment or income-earning opportunities and child health. Several channels can be identified as mechanisms for this relationship. First, higher income earned by women could increase the family's overall income and thereby increase investment in child-care (Atkin, 2009). Second, due to the change in women's earnings, there is also an increase in women's bargaining power in the household, leading to changes in the composition of household investment in public goods. Using data from Mexico, Majlesi (2012) finds that an increase in demand for women's employment in the market is associated with an increase in women's relative decision-making power within the household and that there is an improvement in the reported health condition of their children and decreased likelihood of morbidity. This increase in female-specific earnings could also alter the investment decisions of the mother in their girl or boy child and correct for sex imbalances (Qian, 2008). Third, apart from within-household changes in investment decisions, an increase in local economic development also improves infant health due to better access to healthcare and medical facilities (Benshaul-Tolonen, 2018).

I now explore these plausible mechanisms behind the reduction in neonatal mortality due to such a policy. I test for changes in access to social networks and family planning information due to women's employment, improved fertility outcomes, improved income or bargaining power of the women due to increased earning opportunities, and better access to healthcare.

5.2.1 Employment

Access to social networks and family planning information due to women's employment in the manufacturing sector could be a key determinant of neonatal health. Results in Table 3 show that the employment of women in the high-density regions, post the MFA reform increases by 6-7 percentage points as compared to the low-density regions (columns (1) and (2)). This increase is coming mostly from women employed in the skilled occupation category[24], amounting to an increase in employment by almost 6 percentage points.

An increase in the probability of working for women, while also observing an improvement in the neonatal survival of children could be supported by the fact that women are able to enter and exit the labor market to balance their time between income generating activities and childcare. Ideally to assess if this is indeed the channel through which the health effects are operating, I would need to observe the labor market participation decision of the women before child birth and after. In absence of such data, I look at the labor market participation of women who have had a child in the last 5 years in the data. Based on the age group of children, in Table A6, I do a subsample analysis to check which cohort of women get impacted by the employment boom. I show that on average, the share of women who are in the labor force (overall and in semi-skilled or skilled sectors) at the time of the survey is increasing the age of their children. Only 13% of the women with a child younger than 1 year are working, while this share goes up to 23% for women with a child in the age group of 4-5 years. I show that the employment boom did not impact the women with infant children. However, for women with older children, the probability of working in the high-density regions after the employment boom increases after the shock, suggesting that women are able to go back into the labor market after their childcare needs are met[25]

The employment of men in the sample does not increase, which confirms women's employment as being one of the key channels supporting the neonatal health results.

[24] The coarse occupation data is not available for all years. I have combined skilled and semi-skilled work to proxy for factory work.

[25] These results are only suggestive and should be interpreted with caution, because of low sample sizes, changes in the composition of women in high density regions after the reform - that cannot be tested using the parallel trends assumption due to lack of data, and because the exact channel behind the return to labor market cannot be tested.

5.2.2 Fertility

Prior work by Heath and Mobarak (2015) finds that women who continue to stay close to the garment sector are more likely to postpone marriage and childbirth. This postponement of childbearing decision could mean women have better knowledge about childbirth and improved maternal health which could impact the child's health. The fertility indicator on the extensive margin that I study is the age at first birth in years. On the intensive margin, I consider birth spacing, that is the number of months between any two births, and if the woman is currently pregnant (Chari et al., 2019). The results in Table 3 show that there is a statistically significant and an economically high impact on fertility. Women delay their age at first birth by almost 3 years and wait for more than 10 months between births (which is expected)[26], and there is a lower chance of a woman in the sample being currently pregnant.

5.2.3 Access to Healthcare

The manufacturing growth could also play a role in impacting local health care systems which could affect neonatal health. In Table 5, the results show that there is no effect on improved access to health care. I measure access to health care by several indicators - having a health card, whether the child got any vaccine or not, and whether the mother received any prenatal and antenatal care for the child. There is also no impact on access to information about family planning (there is no change to the family planning information (via radio and television) accessed by the women who gave birth in the 5 years preceding the survey year), or breastfeeding.

5.2.4 Wealth Effects and Women's Bargaining Power

An increase in household wealth could allow women to afford better pre-natal health care for the women and improve the survival rates of neonates. As shown in Table 4, column 1, I find that there is no impact on the wealth index of the household. This index, however, is a measure of the stock of assets owned by the households, which is unlikely to change in response to this policy shock. To measure if on the other hand income for women is rising, I next look at the share of women's income in the household income. I use measures of women's bargaining power as a proxy of their share in the household income. I use the data on the woman having a say in some important household and individual matters, like having

[26] The birth spacing result should, however, be interpreted with caution since Table A3 shows suggestive evidence of lack of parallel trends. These results would, therefore, be biased.

a say in her own health, large household purchases, visits to relatives, and having a say in her child's health. I find that there is an increase in women's bargaining power within the household for matters like visits to relatives and having a say in her child's health which might be a channel explaining the reduced neonatal mortality.

5.3 Sensitivity Analysis

I check the sensitivity of these results to the exposure density and the exposure area. I vary the cut-off for defining clusters as $High\_Density$ ranging from 30 to 80 factories in an interval of 10 factories. Next, I vary the exposure buffer area to 15 Kms. I re-run the regression specification 1 with these varying definitions and plot the coefficient of interest in Figure A3. All the results are robust except for the wealth index for which I find a significant increase in the high-density regions after the policy change for the specifications with 15 Kms buffer area. For all other variables, the results are as expected.

6 Conclusion

The ready-made garment industry in Bangladesh has significantly altered work-related decisions for women in the country. In this paper, I quantify the impact of the employment boom in the industry on the childcare behavior of women and on the survival rates of children. I find that when the trade quota for this industry was removed, employment of women in the areas exposed to the industry expansion increased by 6-7 percentage points. The probability of a child dying in their neonatal age declined by more than 2 percentage points. I argue that these changes are not driven by the selective migration of women with better education, skills, and child survival knowledge, and the results are more widely applicable to women and children who stay close to these employment opportunities. While the data does not allow me to precisely estimate the substitution of a marginal increase in resources within the household from girls to boys, this is an interesting heterogeneity.

An improvement in the neonatal survival of a child could be attributed to several channels, including changes in childbearing decisions of mothers, their access to social networks at workplace, access to non-seasonal jobs close to women's home allowing them to manage childcare duties and labor market participation, or improved bargaining power of women within the household. All these mechanisms combined are likely to be crucial channels in improving neonatal health, more than affecting long-term health outcomes. I find that there are no impacts on the long-term health outcomes of surviving children.

These results have wider implications for the policy discussion around women's work in South Asia. A large proportion of women work in the informal sector where childcare needs are hard to meet and there is an adverse impact on their children's health. However, the results from this paper indicate that in a setting where women's formal paid work in the manufacturing sector, there can still be short-run gains on neonatal health, while keeping the women in the labor force.

7 Tables

Table 1: Summary Statistics

	Num	Mean	Std.Dev.
Child Mortality			
Probability(dying in 1 month from birth)	4150	0.04	0.19
Probability(dying between 1 month and 1 year of birth)	3999	0.01	0.11
Probability(dying between 1 to 5 year of birth)	3948	0.01	0.09
Woman level Characteristics			
Age	6287	28.25	6.34
Years of Education	6284	5.32	4.52
Woman Currently Working in:			
Any Job	6286	0.25	0.43
Any Skilled or Semi-skilled Work	6286	0.12	0.33
Woman has a say in:			
Daily Needs	4312	0.68	0.47
Visits to Relatives	6173	0.70	0.46
Child Health	5700	0.74	0.44
Men level Characteristics			
Currently Working	7307	0.85	0.36
Household level Characteristics			
Wealth Index	6307	3.98	1.31
Urban	6307	0.71	0.45
Fertility Outcomes			
Age at 1st Birth	5655	18.20	3.35
Months between Marriage and 1st Birth	5627	27.94	24.27
Currently Pregnant	5655	0.05	0.22

1. This table has the summary statistics, including the number of non-missing observations, mean, and standard deviation for all variables used in the paper for analysis.
2. Based on a sample of women and men in the age group 18-40.
3. The sample is restricted to only the clusters that have a garment factory in Dhaka and Chittagong.
4. The child mortality indicators are calculated at the child level. The probability of dying in 1 month from birth proxies for neonatal mortality. The probability of dying between 1 month and 1 year of birth proxies for post-neonatal mortality; and the probability of dying between 1 to 5 years of birth proxies child mortality.
5. Age at first birth is measured in years.
6. Currently pregnant is the probability of the woman is currently pregnant.
7. The wealth index is at the household level, and it ranks the economic standing of the surveyed household relative to other households in the survey. It is calculated based on the asset ownership of households and categorizes households into 5 quintiles, with 0 for the poorest households and 5 for the richest households.
8. Urban takes the value 1 if the household belongs to an urban cluster and 0 otherwise.
9. Currently Working for men/women takes the value 1 if they are working in any job and 0 otherwise. For skilled or semi-skilled work, the variable takes the value 1 if the woman works in any skilled or semi-skilled work and 0 otherwise.
10. To proxy bargaining power, I look at the various indicators of a woman having any say in decisions made about her own health, large household purchases, daily needs, visits to relatives and in their child's health.

Table 2: Impact on the probability of dying by age group of children

	<1 year	<1 month	1 month-1 year	<5 years	1-5 year
High x Post	-0.035**	-0.029**	-0.007	-0.033**	0.002
	(0.015)	(0.014)	(0.008)	(0.016)	(0.005)
Observations	4131	4131	3980	4131	3930
Mean Dep. Var.	0.05	0.04	0.02	0.01	0.01

1. The outcome variable is the probability of a child dying in the age-group mentioned in the column name.
2. Based on a sample of children born to women in the age group 18-40.
3. The sample is restricted to only the clusters that have a garment factory in Dhaka and Chittagong.
4. All regressions include the year of birth fixed effects and the cluster fixed effect.
5. All regressions also include baseline information on the population density in 2005 and rainfall in 2005 for each cluster to proxy for time invariant but cluster varying effects.
6. Other covariates include cluster and individual level variables. These are: indicator for whether the cluster is urban or rural, fraction of households with piped water, and the age of the mother.
7. High takes the value 1 for the treated cluster had more than 50 factories in 2004, and saw a high growth in employment opportunities. Post takes the value 1 for values measued after the year 2005.
8. Standard errors are clustered at the cluster level.
9. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3: Impact on labor force participation and fertility outcomes for women

	Currently Working			**Fertility Outcomes**		
	All Women	Women in Skilled Work	All Men	Age at First Birth	Birth Spacing	Currently Pregnant
High x Post	0.065*	0.059***	0.014	3.102***	10.551***	-0.026*
	(0.034)	(0.022)	(0.024)	(0.198)	(1.356)	(0.013)
Observations	6257	6257	7262	5631	5603	5631
Mean Dep. Var.	0.25	0.12	0.85	18.20	27.94	0.05

1. Based on a sample of women and men in the age group 18-40.
2. The sample is restricted to only the clusters that that have a garment factory in Dhaka and Chittagong.
3. Age at first birth is measured in years.
4. Birth spacing is the number of months between marriage and first birth.
5. Currently pregnant is the probability of the woman is currently pregnant.
6. All regressions include the year of birth fixed effects and the proxy-cluster fixed effect.
7. All regressions include the year of birth fixed effects and the cluster fixed effect.
8. All regressions also include baseline information on the population density in 2005 and rainfall in 2005 for each cluster to proxy for time invariant but cluster varying effects.
9. Other covariates include cluster and individual level variables. These are: indicator for whether the cluster is urban or rural, fraction of households with piped water, and the age of the mother.
10. High takes the value 1 for the treated cluster had more than 50 factories in 2004, and saw a high growth in employment opportunities. Post takes the value 1 for values measued after the year 2005.
11. Standard errors are clustered at the cluster level.
12. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4: Impact on household wealth and bargaining power

		Woman has a say about:			
	Wealth Index	Own Health	Large Purchases	Visits to Relatives	Child Health
High x Post	0.020	0.058	0.034	0.066*	0.086**
	(0.124)	(0.038)	(0.034)	(0.036)	(0.033)
Observations	6281	6148	6145	6144	5673
Mean Dep. Var.	3.98	0.65	0.67	0.70	0.74

1. Based on a sample of women in the age group 18-40 who got married before 2005.
2. The sample is restricted to only the clusters that that have a garment factory in Dhaka and Chittagong.
3. The wealth index is at the household level, and it ranks the economic standing of the surveyed household relative to other households in the survey. It is calculated based on the asset ownership of households and categorizes households into 5 quintiles, with 0 for the poorest households and 5 for the richest households.
4. All variables for women's bargaining power are dummy variables that take the value 1 if the woman has an independent or joint say in the mentioned individual or household matter.
5. All regressions include the year of birth fixed effects and the cluster fixed effect.
6. All regressions also include baseline information on the population density in 2005 and rainfall in 2005 for each cluster to proxy for time invariant but cluster varying effects.
7. Other covariates include cluster and individual level variables. These are: indicator for whether the cluster is urban or rural, fraction of households with piped water, and the age of the mother.
8. High takes the value 1 for the treated cluster had more than 50 factories in 2004, and saw a high growth in employment opportunities. Post takes the value 1 for values measued after the year 2005.
9. Standard errors are clustered at the cluster level.
10. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

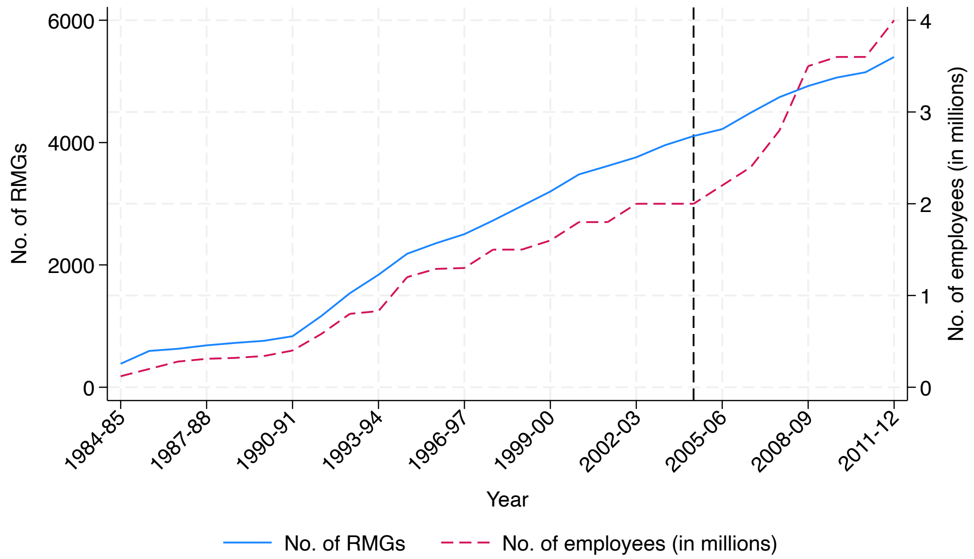
Table 5: Impact on healthcare access and information

	Whether Accessed		**Family Planning Information from**				**Child Care**	
	Antenatal Care	Prenatal Care	Radio	TV	Newspaper	Vaccinated	Health Card	Months Breastfed
High x Post	-0.058	-0.059	0.018	-0.071	-0.043*	-0.016	-0.015	0.861
	(0.046)	(0.046)	(0.029)	(0.049)	(0.025)	(0.027)	(0.048)	(1.035)
Observations	3322	3325	3324	3325	3325	2226	3896	3955
Mean Dep. Var.	0.68	0.68	0.17	0.44	0.07	0.92	0.67	18.84

1. Based on a sample of children born to women in the age group 18-40 who got married before 2005.
2. The sample is restricted to only the clusters that that have a garment factory in Dhaka and Chittagong.
3. I look at health care accessed by women around pregnancy by looking at the indicator variable on whether women accessed Antenatal care or Prenatal care for the child.
4. To measure changes in health information, I look at the probability of accessing family plannig information through various media - specifically radio, TV and newspaper.
5. For child care behavior, I look at the whether the latest child has a health care, or if they are vaccinated and look at the number of month the surviving children were breastfed for. The data for breastfeeding is for all the surviving children.
6. All regressions include the year of birth fixed effects and the proxy-cluster fixed effect.
7. All regressions also include baseline information on the population density in 2005 and rainfall in 2005 for each cluster to proxy for time invariant but cluster varying effects.
8. Other covariates include cluster and individual level variables. These are: indicator for whether the cluster is urban or rural, fraction of households with piped water, and the age of the mother.
9. Information about antenatal care, prenatal care and access to family planning is available only for the latest born.
10. High takes the value 1 for the treated cluster had more than 50 factories in 2004, and saw a high growth in employment opportunities. Post takes the value 1 for values measued after the year 2005.
11. Standard errors are clustered at the cluster level.
12. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

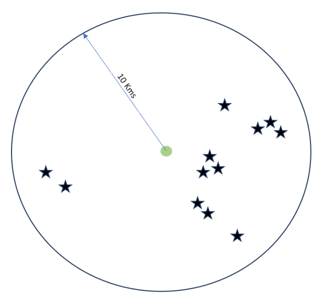
8 Figures

Figure 1: Growth in the RMG sector



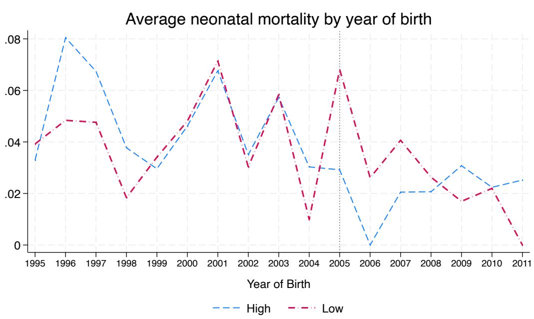
1. Source: Trade Information, Bangladesh Garment Manufacturers and Export Association.
2. The Y axis on the left shows the number of readymade garment factories in Bangladesh over the past years.
3. The second Y axis on the right shows the number of employees in these garment factories.

Figure 2: Defining an individual's exposure to factories - an illustration

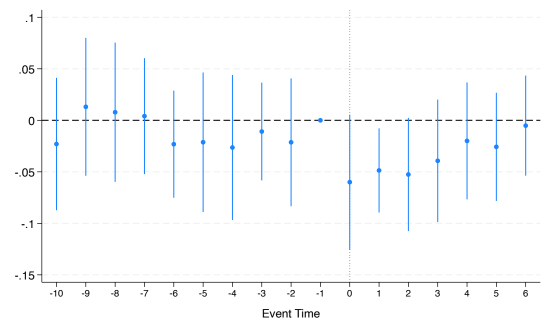


1. This illustration shows the methodology adopted to combine the DHS data with the administrative data on the factories.
2. The green dot in the center represents the clusters where women live. I define a 10 Kms buffer region around the cluster to count the number of factories that women are exposed to. The stars depict the location of the readymade garment factories.
3. I define such a buffer region for each cluster in the sample and count the number of factories inside this region. If the buffer region cluster has more than 50 factories in the pre-reform year of 2004, then I categorize those clusters as high-density or treated clusters. If the buffer region of the cluster has less than 50 factories in 2004, it is defined as the low-density cluster or the control cluster.

Figure 3: Probability of dying within 1 month of birth in clusters that have an RMG factory



(a) Unconditional Means

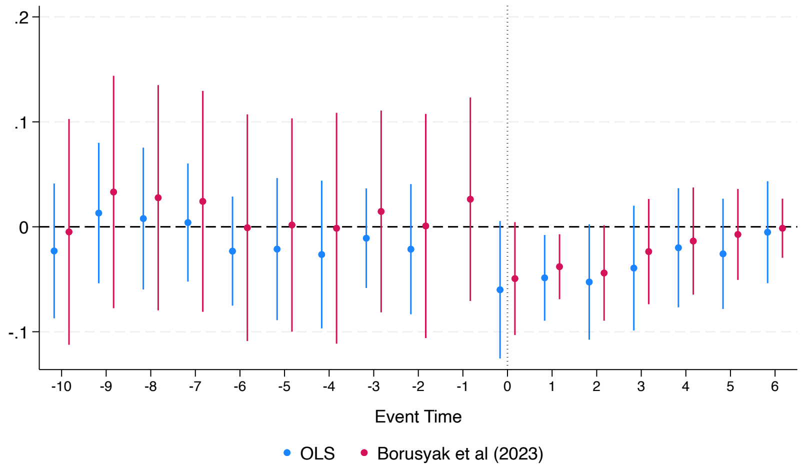


(b) Event Study

1. Neonatal mortality is the probability of a child dying within 1 month of birth.
2. The first figure shows the unconditional mean of neonatal mortality in the high and low-density clusters in pre and post-periods.
3. The second graph tests for parallel trends using a simple event study using an OLS regression with 2004 as the base year.
4. The regression specifications include the child's birth year fixed effects, matched-cluster fixed effects, the mother's age, and cluster-level covariates.
5. These covariates include whether the cluster is urban or rural, baseline cluster characteristics like rainfall and population density in 2005, and the fraction of households in the cluster that have access to piped water.
6. The standard errors are clustered at the cluster level.

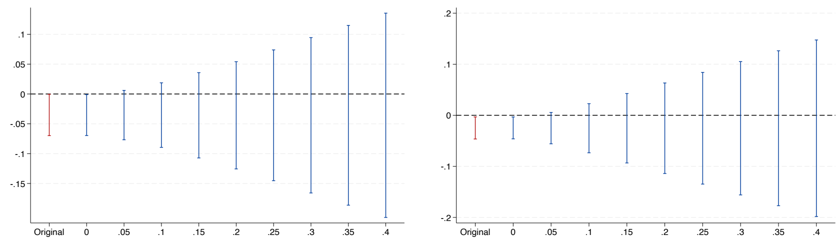
Appendix A - Figures

Figure A1: Parallel Trends by Year of Child Birth: Impact of Employment Boom on Probability of Dying Within 1 Month of Birth



1. This figure shows the test for parallel trends using a simple event study using an OLS regression with the base 2004, and the robustness of these results using the imputation method by Borusyak et al (2023).
2. These event study plots are by the year of birth of the child.
3. The regression specifications include the child's birth year fixed effects, matched-cluster fixed effects, and individual and cluster-level covariates.
4. Individual covariates include the age of the mother.
5. Cluster level covariates include whether the cluster is urban or rural, baseline cluster characteristics like rainfall and population density in 2005, and the fraction of households in the cluster that have access to piped water.
6. The standard errors are clustered at the cluster level.

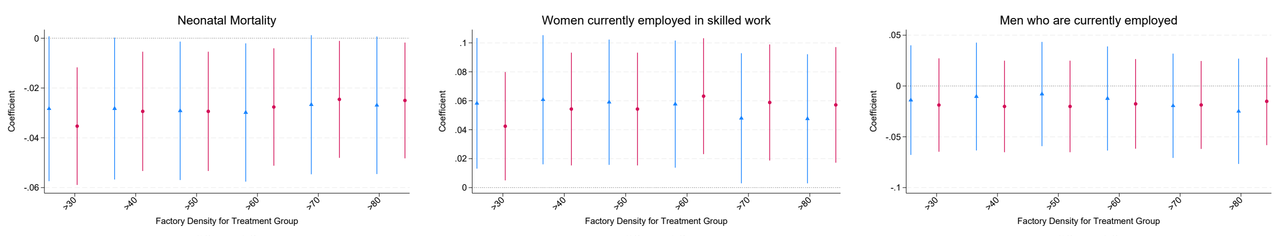
Figure A2: Robustness: Impact of Employment Boom on Neonatal Mortality in Violation of Parallel Trends Assumption



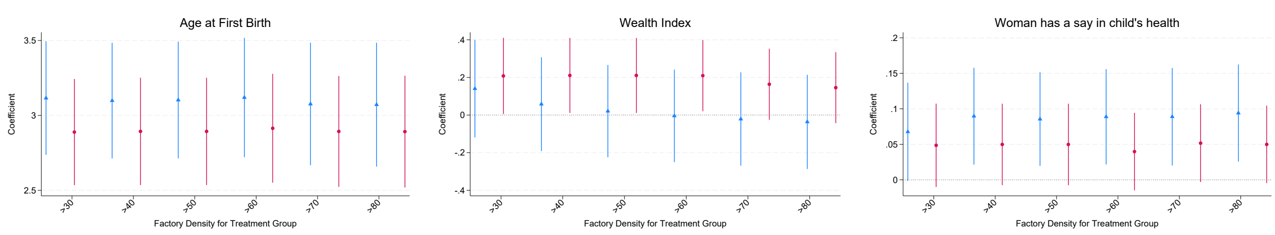
(a) OLS (b) Borusyak et al (2023)

1. The first figure shows the robustness of the effects estimated using an OLS specification to Rambachan and Roth (2022).
2. The second figure does the same for effects estimated using the imputation method by Borusyak et al (2023).
3. The results are evaluated under smoothness restrictions that account for parallel trends assumption violation.
4. The regression specifications include the child's birth year, matched-cluster fixed effects, the mother's age, and cluster-level covariates.
5. These covariates include whether the cluster is urban or rural, baseline cluster characteristics like rainfall and population density in 2005, and the fraction of households in the cluster that have access to electricity and piped water.
6. The standard errors are clustered at the DHS cluster level.

Figure A3: Sensitivity to the cut-off number of factories and the radius



(a) (b) (c)



(d) (e) (f)

1. These figures show the sensitivity of the estimated results to the varying buffer region from households to measure the distance to factories, and the varying selected threshold level of factories within a cluster buffer region to define low and high-density clusters.
2. The regression specifications are the same as those used for the main analysis.
3. Depending on the specification, the regressions include the child's birth year fixed effects, or the survey year fixed effect, matched-cluster fixed effects, the age of the mother, and cluster-level covariates.
4. These covariates include whether the cluster is urban or rural, baseline cluster characteristics like rainfall and population density in 2005, and the fraction of households in the cluster that have access to piped water.
5. The standard errors are clustered at the cluster level.

Appendix A - Supplementary Tables

Table A1: Comparison of factories geocoded with those not geocoded

	No. of management employees		**No. of machines**		**Prod. Capacity (Yearly in 100 dozen)**	
	Geocoded	Not Geocoded	Geocoded	Not Geocoded	Geocoded	Not Geocoded
Mean	647.68	386.54	308.73	153.75	7747.12	2438.79
Median	370	300	172	115	800	600
Min	0	0	0	0	0	0
Max	27772	3000	10070	852	1533333	130000
N	2678	229	1509	187	1235	150

1. This data is from the individual factory-level information available from the data that was web-scraped from the BGMEA website.
2. This table compares the summary statistics, specifically the mean, median, and range of the factories whose addresses I was able to geocode with those of the factories I was unable to locate on the map.
3. This information is not available for all the factories, and I only compare the values based on the available data.
4. N is the number of factories with non-missing data on the attributes considered.

Table A2: Difference between High and Low Density Clusters

	Low Density	High Density	Difference (High-Low)
Child Mortality	0.011	0.007	-0.004
	(0.104)	(0.084)	(0.004)
Postneonatal Mortality	0.014	0.021	0.007
	(0.118)	(0.143)	(0.006)
Neonatal Mortality	0.040	0.051	0.011
	(0.197)	(0.221)	(0.009)
Age at 1st Birth	17.790	18.189	0.399***
	(3.208)	(3.378)	(0.132)
Months between Marriage and 1st Birth	28.768	29.785	1.018
	(26.188)	(25.353)	(1.033)
Currently Pregnant	0.060	0.057	-0.004
	(0.238)	(0.231)	(0.009)
Wealth Index	3.106	4.391	1.285***
	(1.409)	(1.067)	(0.047)
Urban	0.353	0.962	0.609***
	(0.478)	(0.191)	(0.013)
Men Currently Working	0.853	0.827	-0.026**
	(0.354)	(0.378)	(0.013)
Woman Currently Working	0.233	0.279	0.046***
	(0.423)	(0.449)	(0.017)
Woman in Any Skilled or Semi-skilled Work	0.051	0.116	0.065***
	(0.219)	(0.320)	(0.011)
Woman Has a Say: Own Health	0.559	0.584	0.024
	(0.497)	(0.493)	(0.019)
Woman Has a Say: Household Purchases	0.568	0.682	0.114***
	(0.496)	(0.466)	(0.018)
Woman Has a Say: Daily Needs	0.596	0.687	0.091***
	(0.491)	(0.464)	(0.018)
Woman Has a Say: Visits to Relatives	0.621	0.690	0.069***
	(0.485)	(0.463)	(0.018)
Woman Has a Say: Child Health	0.641	0.696	0.055***
	(0.480)	(0.460)	(0.018)
Woman's Age	28.348	28.364	0.016
	(6.249)	(6.217)	(0.239)
Woman's Years of Education	3.811	5.123	1.313***
	(4.160)	(4.589)	(0.170)

1. This table shows the difference between the variables in the low and high density clusters in the pre-period.
2. Column (2) and (3) show the means in low and high density clusters respectively.
3. Column (3) states the difference between high and low, and performs a t-test of the difference.
4. The standard errors are in the parenthesis.
5. Based on a sample of women and men in the age group 18-40.
6. The sample is restricted to only the clusters that ever get a factory in Dhaka and Chittagong.
7. Neonatal Mortality takes the value 1 when child dies within 1 month of being born, and 0 otherwise.
8. Post-neonatal Mortality is defined as 1 if the child dies between 1 month of birth and before they are 1 year old
9. Child Mortality is defined as 1 if the child dies between 1 to 5 years of birth
10. Age at first birth is measured in years.
11. Currently pregnant is the probability of the woman is currently pregnant.
12. The wealth index is at the household level, and it ranks the economic standing of the surveyed household relative to other households in the survey. It is calculated based on the asset ownership of households and categorizes households into 5 quintiles, with 0 for the poorest households and 5 for the richest households.
13. Urban takes the value 1 if the household belongs to an urban cluster and 0 otherwise.
14. Currently Working for men/women takes the value 1 if they are working in any job and 0 otherwise. For skilled or semi-skilled work, the variable takes the value 1 if the woman works in any skilled or semi-skilled work and 0 otherwise.
15. To proxy bargaining power, I look at the various indicators of a woman having any say in decisions made about her own health, large household purchases, daily needs, visits to relatives and in their child's health.
16. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A3: Leads and Lags of program effects on neontatal mortality, women's and men's work, women's fertility and health care behavior

	Neonatal Mortality	Women Currently Working	Men Currently Working	Age at 1st birth	Birth Spacing	Currently Pregnant	Breastfeeding
High	-0.0001	-0.0178	0.0779*	-0.4039	2.0612	0.0127	0.4631
	(0.0291)	(0.0552)	(0.0428)	(0.4496)	(2.4465)	(0.0228)	(1.3718)
1999	-0.0091	0.0362	-0.0829***	0.0467	-0.5020	0.0115	-0.0840
	(0.0140)	(0.0385)	(0.0231)	(0.2011)	(1.4366)	(0.0132)	(1.0030)
High × 1999	0.0148	-0.0011	0.0133	0.4678	5.4575***	-0.0147	-1.6209
	(0.0202)	(0.0470)	(0.0303)	(0.3095)	(1.9132)	(0.0179)	(1.2812)
2007	-0.0015	0.0679	-0.0072	0.0163	-0.0969	0.0181	-0.0733
	(0.0191)	(0.0475)	(0.0243)	(0.2144)	(1.3646)	(0.0194)	(1.0646)
High × 2007	-0.0321	-0.0219	-0.0025	0.9610***	1.2031	-0.0417*	0.7648
	(0.0227)	(0.0599)	(0.0324)	(0.3112)	(1.8585)	(0.0230)	(1.3090)
2011	-0.0276*	-0.1060***	-0.0309	0.0130	-7.2305***	-0.0098	-0.6147
	(0.0148)	(0.0305)	(0.0244)	(0.2389)	(1.6541)	(0.0140)	(1.1394)
High × 2011	-0.0143	0.1210***	0.0284	0.7312**	5.1322**	-0.0282	1.1256
	(0.0191)	(0.0442)	(0.0323)	(0.3250)	(2.0307)	(0.0173)	(1.3947)
Observations	4131	6257	7262	5631	5603	5631	3955

1. This table checks for the parallel trends assumptions using the leads and lags model.
2. The baseline is 2004.
3. Based on a sample of children born to women in the age group 18-40.
4. The sample is restricted to only the clusters that that have a garment factory in Dhaka and Chittagong.
5. All regressions include baseline information on the population density in 2005, rainfall in 2005 for each cluster.
6. Other cluster variables are whether the cluster is urban or rural, fraction of households with piped water, age of the woman.
7. High takes the value 1 for the treated cluster had more than 50 factories in 2004, and saw a high growth in employment opportunities.
8. Standard errors are clustered at the cluster level.
9. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A4: Leads and Lags of program effects on household wealth and bargaining power of women

		Woman has a say			
	Wealth Index	Own Health	Large Household Purchases	Visits to Relatives	Child Health
High	0.1495	-0.1524*	-0.1674**	-0.1780**	-0.1114
	(0.2491)	(0.0801)	(0.0780)	(0.0718)	(0.0741)
1999	-0.0526	0.0875**	0.0027	0.0084	0.0393
	(0.1486)	(0.0438)	(0.0454)	(0.0491)	(0.0414)
High × 1999	0.2014	0.0008	-0.0143	-0.0225	-0.0110
	(0.1679)	(0.0575)	(0.0541)	(0.0571)	(0.0503)
2007	-0.0967	0.1531***	0.0997**	0.0777	0.1015**
	(0.1747)	(0.0433)	(0.0484)	(0.0478)	(0.0510)
High × 2007	0.4736**	0.0512	-0.0083	0.0371	0.0831
	(0.1941)	(0.0520)	(0.0554)	(0.0547)	(0.0559)
2011	0.2852*	0.1475***	-0.0057	0.0147	0.0789*
	(0.1507)	(0.0496)	(0.0524)	(0.0520)	(0.0457)
High × 2011	-0.0907	0.0640	0.0490	0.0657	0.0772
	(0.1664)	(0.0583)	(0.0577)	(0.0577)	(0.0510)
Observations	6281	6148	6145	6144	5673

1. This table checks for the parallel trends assumptions using the leads and lags model.
2. The baseline is 1999.
3. Based on a sample of children born to women in the age group 18-40.
4. The sample is restricted to only the clusters that that have a garment factory in Dhaka and Chittagong.
4. All regressions include baseline information on the population density in 2005, rainfall in 2005 for each cluster.
5. All regressions include baseline information on the population density in 2005, rainfall in 2005 for each cluster.
6. Other cluster variables are whether the cluster is urban or rural, fraction of households with piped water, age of the woman.
7. High takes the value 1 for the treated cluster had more than 50 factories in 2004, and saw a high growth in employment opportunities.
8. Standard errors are clustered at the cluster level.
9. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A5: Impact on long term health outcomes of surviving children

	Height-for-Age	Weight-for-Age	Weight-for-Height
High x Post	0.089	0.044	0.004
	(0.125)	(0.110)	(0.090)
Observations	3491	3491	3491
Mean Dep. Var.	-1.54	-1.65	-0.92

1. Based on a sample of children born to women in the age group 18-40.
2. The sample is restricted to only the clusters that that have a garment factory in Dhaka and Chittagong.
3. Height-for-Age, Weight-for-Age and Weight-for-Height are Z-scores for surviving children.
4. All regressions include the year of birth fixed effects and the proxy-cluster fixed effect.
5. All regressions also include baseline information on the population density in 2005 and rainfall in 2005 for each cluster to proxy for time invariant but cluster varying effects.
6. Other covariates include cluster and individual level variables.
7. These are: indicator for whether the cluster is urban or rural, fraction of households with piped water, and the age of the mother.
8. High takes the value 1 for the treated cluster had more than 50 factories in 2004, and saw a high growth in employment opportunities. Post takes the value 1 for values measued after the year 2005.
9. Standard errors are clustered at the cluster level.
10. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A6: Impact on female labor force participation based on the age of child

	0-1 year	1-2 year	2-3 year	3-4 year	4-5 year
Probability(Working Currently)					
High x Post	-0.003	0.175**	0.122*	0.075	0.080
	(0.058)	(0.078)	(0.065)	(0.061)	(0.067)
Probability(Working in Skilled Job)					
High x Post	0.002	0.110**	0.078*	0.065*	0.066*
	(0.033)	(0.048)	(0.040)	(0.037)	(0.039)
Observations	786	864	837	863	841
Mean Prob.(Working Currently)	0.13	0.16	0.20	0.23	0.23
Mean Prob.(Working in Skilled Job)	0.05	0.07	0.09	0.11	0.12

1. Based on a sample of women who have a surviving child of the relevant age group in the retrospective birth history data.
2. The sample is restricted to only the clusters that ever had a garment factory in Dhaka and Chittagong.
3. Neonatal Mortality is defined as 1 if the child dies within 1 month of birth.
4. All regressions include the year of survey fixed effects and the cluster fixed effect.
5. All regressions also include baseline information on the population density in 2005 and rainfall in 2005 for each cluster to proxy for time invariant but cluster varying effects.
6. Other covariates include cluster and individual level variables. These are: indicator for whether the cluster is urban or rural and the fraction of households with piped water.
7. High takes the value 1 for the treated cluster had more than 50 factories in 2004, and saw a high growth in employment opportunities. Post takes the value 1 for values measued after the year 2005.
8. Standard errors are clustered at the cluster level.
9. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A7: Impact on neonatal mortality amongst non-migrant mothers

	All Children	Boys	Girls
High x Post	-0.027*	-0.067***	0.021
	(0.015)	(0.020)	(0.021)
Observations	3647	1877	1770
Mean Dep. Var.	0.04	0.04	0.04

1. Based on a sample of children born to women in the age group 18-40 who got married before 2005.
2. The sample is restricted to only the clusters that that have a garment factory in Dhaka and Chittagong.
3. Neonatal Mortality is defined as 1 if the child dies within 1 month of birth.
4. All regressions include the year of birth fixed effects and the cluster fixed effect.
5. All regressions also include baseline information on the population density in 2005 and rainfall in 2005 for each cluster to proxy for time invariant but cluster varying effects.
6. Other covariates include cluster and individual level variables. These are: indicator for whether the cluster is urban or rural, fraction of households with piped water, and the age of the mother.
7. High takes the value 1 for the treated cluster had more than 50 factories in 2004, and saw a high growth in employment opportunities. Post takes the value 1 for values measued after the year 2005.
8. Standard errors are clustered at the cluster level.
9. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

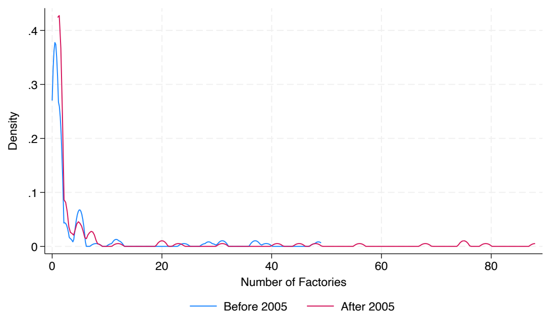
Table A8: Impact on labor force participation of non-migrant women

	All Women	Women in Skilled Work
High x Post	0.056	0.061***
	(0.038)	(0.023)
Observations	5557	5557
Mean Dep. Var.	0.26	0.12

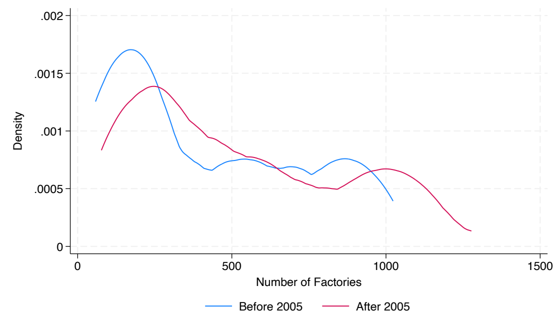
1. Based on a sample of women in the age group 18-40 who got married before 2005.
2. The sample is restricted to only the clusters that that have a garment factory in Dhaka and Chittagong.
3. All regressions include the year of birth fixed effects and the cluster fixed effect.
4. All regressions also include baseline information on the population density in 2005 and rainfall in 2005 for each cluster to proxy for time invariant but cluster varying effects.
5. Other covariates included are cluster and individual level variables. These are: indicator for whether the cluster is urban or rural, fraction of households with piped water, and the age of the mother.
6. High takes the value 1 for the treated cluster had more than 50 factories in 2004, and saw a high growth in employment opportunities. Post takes the value 1 for values measued after the year 2005.
7. Standard errors are clustered at the cluster level.
8. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Appendix B - Supplementary Figures

Figure B1: Distribution of Factories



(a) Low Density Clusters



(b) High Density Clusters

1. These density graphs show the distribution of the number of factories in the low and high density clusters in the year 2004 - one year before the policy shock, and after the policy shock until 2011.
2. High density clusters are defined as clusters with more than 50 factories in 2004. Low density clusters are defined as clusters with less than 50 factories in 2004.
3. These graphs show the increase in the number of factories in high density clusters was more, while the distribution of factories in the low density clusters did not change much after the liberalization policy.

Appendix C - Web scraping of Factory Data

There were some limitations in geocoding the exact addresses, and I could only locate them to the centroid of their lowest identified neighborhood (mostly police wards/subdistricts[27] or cities/towns within a subdistrict). The trade union currently has 4370 members, of which I geocoded a total of about 4000 factories. After several rounds of cleaning the addresses, I ended up identifying factories in 288 neighborhoods[28]. The police ward is missing for 353 factories.

Given that the factory geocoding is imprecise and only recognizable until the police ward or the town within a sub-district level[29], effectively, the clusters that lie close to the town/police ward center, could get identified as high density even though they might be low density (since the centroid is getting counted as a factory). On the other hand, some high-density clusters might be identified as low-density because the centroid of the town/police ward lies outside the buffer area. The direction of the measurement bias arising due to this is thus ambiguous.

I geocoded the addresses of 109 factories manually to compare the precision of geocoding done using Google API. 33% of the factories have a difference of 0-2km between the manual geocoding and the one using software; 27.5% of them differ by 2-5kms. 22.9% differ by 5-10kms; 5.5% of the factories are displaced by 10-20kms and the rest of the 11% are displaced by more than 20kms (ranging from 47kms to 260kms)[30]. In general, given this measurement error, the robustness of the results can be checked using varying the buffer region of the clusters, except for very large distances. For a distance of 15 Km, the results are robust as shown.

[27] Since 1982, the police wards have been redesignated as sub-districts.

[28] Kagy (2014) her paper on the impact of this policy on children's education outcomes uses the same list of factories for her analysis but identifies 327 neighborhoods. It is worth noting that the author scraped the list at a different time.

[29] In the DHS data, the police ward or sub-district identifier is missing for 1999. Also, the police wards or sub-districts that are part of the sample for the later DHS sample years are not the same. The survey, typically, sampled 1-3 clusters within a police ward.

[30] The factories that are displaced by a large amount are concentrated in a few districts – 3 in Chattogram, 4 in Dhaka, 1 in Gaibandha and 4 in Gazipur. I next check how many clusters in these districts are low density and high density. Most of the clusters in these districts are high-density clusters.

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