Bangladesh Immunization Divide: Going beyond rural, urban , and regional differences?

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1. Introduction:

The year 2015 is an interesting year as low and middle income countries around the globe will take a stock of their achievements with regard to millennium development goals. While Bangladesh has made rapid progress in meeting its target towards child health outcomes, it is widely known that regional differences persist. Hence a child is Khulna division has a very high probability of being vaccinated as against a child in the Sylhet division. Rural-urban differences when it comes to maternal and child health outcomes are also fairly known. Apart from regional, and rural urban differences, individual and household factors that influence full vaccination rates are also known. However, it may not be feasible for program planners and health planners to target household and individual factors, but instead they need to known community level factors that affect full vaccination coverage. Just classifying a landscape based on rural-urban or regional divide is not enough as there would be several pockets of communities with high vaccination coverage in low performing regions and vice-versa. In this context, targeting community level factors becomes very important to scale vaccination coverage. This view is also shared by the World Health Organization's recent motto on 'Reach Every Community' as there is now a growing recognition that district level vaccination indicators often mask the variation in at the community level. The purpose of this research is:

i) Examine the factors that explain variation in full immunization coverage at the community level. Having knowledge of geographic predictors at the community level can help health planners in Bangladesh address gaps in country's health system related to disparity and inequities that persist in the health system
ii) Investigate why some pockets of communities within hard to reach areas of Bangladesh are better served by the Expanded Program on Immunization while other communities continue to have low coverage
iii) Apply spatial interpolation to predict pockets of communities in the Upazilla (sub-district) that have low vaccination coverage

2. Country Context:

Bangladesh is located in the largest delta region of the world, formed by the river Ganges and Brahmaputra. About 14000 sq kilometers of area is bordered by Bay of Bengal to the south, India to its west and Myanmar to its south east. The country has hilly tracks mostly in Chittagong and Sylhet region, while the most part of the country is almost flat. These hilly regions and the low lying area (haor),which are the hardest to reach areas in the country have an estimated population of 14 million. It is estimated that complete immunization coverage in these hard to reach districts is merely in the range of 40 to 60 percent (Uddin et al., 2012). This reflects a serious need to capture these regions which are under-immunized considering that overall country estimates are over 90 percent for most vaccines.

In response to growing concern about poor health indicators in these hard to reach districts, since 2006 there have been interventions that are going on. For instance, since 2006 UNICEF identified 14 of these low performing or hard to reach districts which ranked poor on certain vaccination indicators. Similarly in 2007, WHO also launched intervention in another 23 districts to boost the vaccination coverage. Based on these interventions one would expect the gap in coverage to have narrowed down. In spite of this, based on the 2011 DHS data, we see that most communities with below 70 percent coverage fall within the intervention districts and most communities with full immunization coverage fall outside of these intervention districts. But this does not tell the full story.

East-West Immunization Gap:

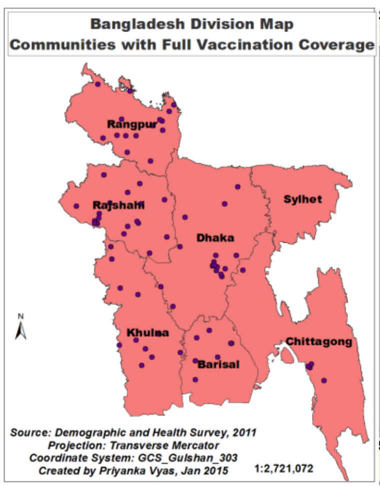

Figure 1

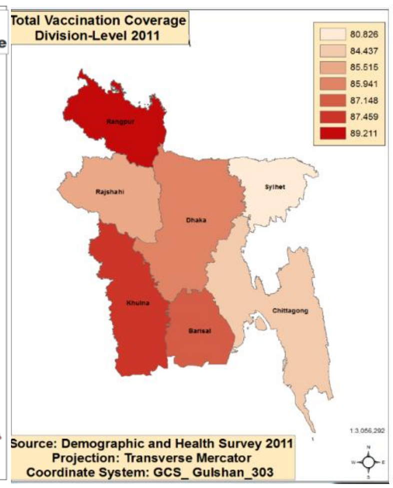

Figure 2

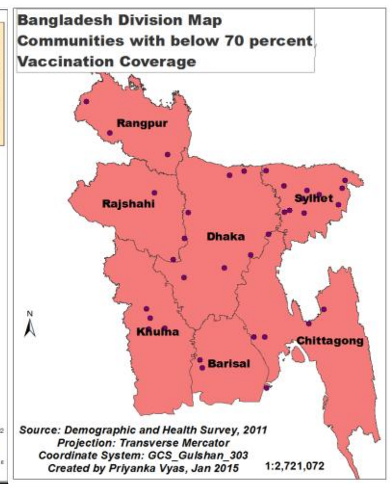

Figure 3

Vaccination coverage among communities within the intervention district and outside:

A closer examination of vaccination coverage at the community level reveals that there are communities with low coverage in better performing regions and vice versa. Then the question is: What community level factors affect full immunization coverage?

3. Data sources:

Figure 4 to the right shows the map of study area. There are 600 points, each of which represents a community of 20-30 households. Thus there are 17,000 households and 600 point locations. Attribute data for community and the spatial point data are from the latest Demographic and Health Survey, 2011 for Bangladesh. We obtained actual administrative layers for all the villages, unions, thanas, and districts from the Bangladesh Bureau of Statistics. This makes it possible for us to do our analysis using actual administrative boundaries, making this study more relevant for policy purposes.

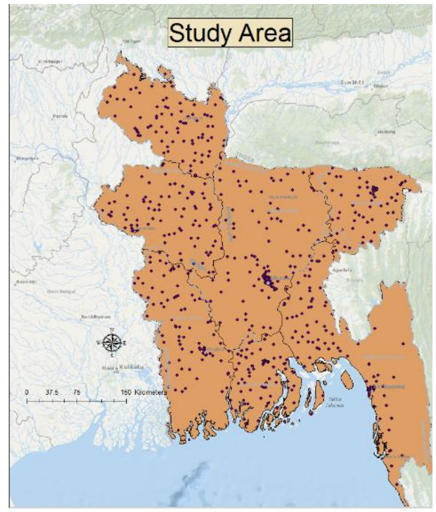

Fig 4

4. Literature review:

Several papers have examined the problem of child immunization coverage, of which few have focused specifically with regard to hard to reach areas. One article that discussed child immunization divide examined factors such as gender, rural-urban difference, mother's education, supply side factors such as proximity to the health center, insufficient supply of the vaccine, and absence of EPI workers during immunization campaigns (Chowdhury, Bhuiya, Mahmud, Abdus Salam, & Karim, 2003). Another article attributes the success in vaccination coverage to the Bangladesh's unique model of community health workers.(El Arifeen et al., 2013). Studies examining cross-country variation have found community health worker density and density of doctors and nurses to be significant. Research that specifically examines factors associated with low coverage in rural and hard to reach areas have found that low availability of health workers in these areas, cancelled immunization session play an important role. (Uddin et al., 2012b). A selected number of studies have applied spatial determinants such as distance, travel time, or used street network analysis to investigate the issue of low coverage in certain areas(Okwaraji et al. 2012, Sasaki, Satoshi et al. 2011). A ward-level study—the lowest administrative unit in Bangladesh--- found significant cluster of childhood deaths in low lying areas of Chakaria, suggesting the role of geographical determinants that influence provision of key health services, which in turn affect health outcomes such as mortality(Hanifi, Haq, Aziz, & Bhuiya, 2010).

5. Methodology and variables:

Variable name	**Code**	**Method**
Total vaccination coverage	Vac, unvac	Based on the total number of children in each household and the total number of households in each community/cluster, we calculated the number of eligible doses of vaccines per child and per household. We calculated the number of

		administered doses per child and per household. These were aggregated at the community level or cluster level to obtain the counts of children that were vaccinated and those that were not.
Wealth Index	Wlth_ind	This is the mean wealth index at the community level
Rural-Urban	Urban_RURA	Whether the community is located in rural or urban area
Type of road		Factor variable if the community had access to an all weather road, seasonal road, waterway, or just a path.
Community health workers	Cbh_tot	Number of community health workers in the community
Micro financing or income generating activities	Mfi_tot	Number of micro finance or income generating organizations in the community.
Distance to the nearest Thana Health Center	Thct_fac1	Factor variable if the distance from the Thana health center is less than 40 minutes, between 40 to 90 minutes, or more than 90 minutes to the community
Distance to nearest hospital	hosp_fac1	Factor variable if the distance from the nearest hospital is less than 40 minutes, between 40 to 90 minutes, or more than 90 minutes to the community

Table1:

Table 1 shows the variables used in the model and how they were created. Table2 shows the results from binomial regression without any spatial effect:

```
Call:
glm(formula = cbind(pts$vac, pts$unvac) ~ pts$wlth_ind + pts$co107 +
    pts$URBAN_RURA + pts$cbh_tot + pts$mfi_tot + pts$thct_fac1 +
    pts$hosp_fac1, family = binomial)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-10.388   -1.402    0.527    2.366    8.934

Coefficients:
                                                                 Estimate Std. Error z value Pr(>|z|)
(Intercept)                                                     1.466e+00  6.762e-02  21.673  < 2e-16 ***
pts$wlth_ind                                                    2.454e-07  1.650e-08  14.875  < 2e-16 ***
pts$co107other                                                 -4.992e-01  1.908e-01  -2.616  0.00889 **
pts$co107path                                                  -9.613e-01  8.555e-02 -11.237  < 2e-16 ***
pts$co107seasonal                                              -6.356e-02  2.863e-02  -2.220  0.02642 *
pts$co107waterway                                              -2.334e-01  5.916e-02  -3.946 7.96e-05 ***
pts$URBAN_RURAU                                                -2.222e-01  3.470e-02  -6.403 1.52e-10 ***
pts$cbh_tot                                                     1.196e-01  1.260e-02   9.494  < 2e-16 ***
pts$mfi_tot                                                     6.137e-02  6.748e-03   9.095  < 2e-16 ***
pts$thct_fac1Thana Health Center is less than or equal to 40 min -2.060e-03  3.393e-02  -0.061  0.95159
pts$thct_fac1Thana Health Center is more than 40 min            2.318e-02  4.006e-02   0.579  0.56286
pts$thct_fac1Thana Health Center is more than 90 min           -5.996e-01  4.929e-02 -12.165  < 2e-16 ***
pts$hosp_fac1Nearest hospital is less than or equal to 60 min   2.104e-02  5.312e-02   0.396  0.69207
pts$hosp_fac1Nearest hospital is more than 120 min             -2.916e-02  5.956e-02  -0.490  0.62446
pts$hosp_fac1Nearest hospital is more than 60 min              -8.017e-02  5.628e-02  -1.424  0.15433
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 6180.8  on 599  degrees of freedom
Residual deviance: 4904.5  on 585  degrees of freedom
AIC: 7123.5

Number of Fisher Scoring iterations: 5
```

Table2:

Since our response variable is the form of number of successes and the number of failures, we decided to use binomial model to test without any spatial effect. The results show that wealth index at the community level is positively correlated with the vaccination coverage and is very significant. The type of road a community has access to is important for vaccination coverage as it is also a proxy for whether a community is located in a hard to reach area or not. The intercept is positive and very significant as it would represent community which has access to an access to an all weather type of road. Community health workers and presence of micro financing or income generating organizations are significant and have a positive effect on vaccination coverage. With regard to distance to health facility, we find that if the community is located more than 90 minutes from the Thana Health Center it has a negative effect on vaccination coverage, but distance to the hospital is not a significant predictor. This means that hospitals don't play a much crucial role but the location of the communities with regard to the Thana or the sub-district health center matters. This is also logical based on the principles of urban hierarchy and health care delivery. Hospital offers a higher order service and is not a very important source for low level service like immunization but a Thana health center which is within a radius of 10-15 kilometers plays a more vital role in transporting and storage of vaccines.

Next I test the results with the spatial model. Since we overlay the communities on the second lowest administrative boundaries, which is the union level, we decided to go with distance based neighbors. Since all the communities surveyed were not connected with contiguous boundaries, I defined the minimum threshold distance to ensure each community had at least four neighbors.

Moran test indicated low positive spatial autocorrelation but very significant.

```
 Moran's I test under randomisation

data:  bd.atr$tpct
weights: bd.dnblists

Moran I statistic standard deviate = 4.7838, p-value = 8.601e-07
alternative hypothesis: greater
sample estimates:
Moran I statistic       Expectation          Variance
     4.048384e-02     -1.669449e-03      7.764555e-05
```

Fig 6

In the next two tables, we ran the spatial lag and the spatial error model. We find that these models outperformed because the autocorrelation component was high in the spatial error model and very significant. It was lower in the lag model but was still significant. The AIC in these models was also lower. In table 3, among the type of road factors, path road has a very significant and a negative effect as it shows that communities really lack accessibility to reach there through a paved road. Wealth index, community health workers, and distance from the Thana health center to more than 90 minutes remained significant. All other factors became insignificant especially the rural urban differences. These results remained consistent even with spatial lag model even though the autocorrelation component displayed in the model was fairly low.

```
Call:errorsarlm(formula = pts$tpct ~ pts$wlth_ind + pts$co107 + pts$URBAN_RURA +
    pts$cbh_tot + pts$mfi_tot + pts$thct_fac1 + pts$hosp_fac1,     listw = bd.dnblists, tol.solve = 1.8e-15)

Residuals:
     Min       1Q   Median       3Q      Max
-34.6732  -5.8232   1.0048   7.0027  23.1367

Type: error
Coefficients: (asymptotic standard errors)
                                                                 Estimate  Std. Error z value  Pr(>|z|)
(Intercept)                                                    8.4338e+01  2.3282e+00 36.2245 < 2.2e-16
pts$wlth_ind                                                   2.7225e-06  6.3196e-07  4.3080 1.647e-05
pts$co107other                                                -1.3216e+01  9.7439e+00 -1.3563 0.1749895
pts$co107path                                                 -1.5038e+01  4.4807e+00 -3.3562 0.0007903
pts$co107seasonal                                             -4.7276e-01  9.8843e-01 -0.4783 0.6324412
pts$co107waterway                                             -3.5554e+00  2.5592e+00 -1.3892 0.1647601
pts$URBAN_RURAU                                               -2.2499e+00  1.1379e+00 -1.9773 0.0480092
pts$cbh_tot                                                    9.0962e-01  4.0066e-01  2.2703 0.0231899
pts$mfi_tot                                                    4.1577e-01  2.4706e-01  1.6829 0.0924006
pts$thct_fac1Thana Health Center is less than or equal to 40 min  4.7234e-02  1.0863e+00  0.0435 0.9653179
pts$thct_fac1Thana Health Center is more than 40 min          -2.1670e-01  1.2983e+00 -0.1669 0.8674399
pts$thct_fac1Thana Health Center is more than 90 min          -7.3541e+00  1.9434e+00 -3.7841 0.0001543
pts$hosp_fac1Nearest hospital is less than or equal to 60 min  1.6736e-01  1.7390e+00  0.0962 0.9233306
pts$hosp_fac1Nearest hospital is more than 120 min             3.9719e-01  2.0383e+00  0.1949 0.8455025
pts$hosp_fac1Nearest hospital is more than 60 min             -5.1191e-01  1.8419e+00 -0.2779 0.7810718

Lambda: 0.40051, LR test value: 7.8406, p-value: 0.0051085
Asymptotic standard error: 0.12425
    z-value: 3.2233, p-value: 0.0012673
Wald statistic: 10.39, p-value: 0.0012673

Log likelihood: -2208.71 for error model
ML residual variance (sigma squared): 91.786, (sigma: 9.5805)
Number of observations: 600
Number of parameters estimated: 17
AIC: 4451.4, (AIC for lm: 4457.3)
```

Table 3

```
Call:lagsarlm(formula = pts$tpct ~ pts$wlth_ind + pts$co107 + pts$URBAN_RURA +
    pts$cbh_tot + pts$mfi_tot + pts$thct_fac1 + pts$hosp_fac1,     listw = bd.dnblists, tol.solve = 1.8e-15)

Residuals:
     Min       1Q   Median       3Q      Max
-35.6765  -5.7580   1.0820   6.8137  22.6034

Type: lag
Coefficients: (asymptotic standard errors)
                                                                 Estimate  Std. Error z value  Pr(>|z|)
(Intercept)                                                    7.8966e+01  3.0938e+00 25.5241 < 2.2e-16
pts$wlth_ind                                                   2.1836e-06  6.0617e-07  3.6022 0.0003156
pts$co107other                                                -1.2518e+01  9.8103e+00 -1.2761 0.2019343
pts$co107path                                                 -1.4919e+01  4.5151e+00 -3.3042 0.0009524
pts$co107seasonal                                             -6.6009e-01  9.8802e-01 -0.6681 0.5040708
pts$co107waterway                                             -3.4321e+00  2.5742e+00 -1.3333 0.1824472
pts$URBAN_RURAU                                               -1.9629e+00  1.1399e+00 -1.7220 0.0850704
pts$cbh_tot                                                    1.0648e+00  3.9948e-01  2.6655 0.0076880
pts$mfi_tot                                                    5.7785e-01  2.3908e-01  2.4170 0.0156507
pts$thct_fac1Thana Health Center is less than or equal to 40 min -2.0875e-01  1.0794e+00 -0.1934 0.8466448
pts$thct_fac1Thana Health Center is more than 40 min          -4.3344e-01  1.2942e+00 -0.3349 0.7376925
pts$thct_fac1Thana Health Center is more than 90 min          -8.0730e+00  1.9515e+00 -4.1369  3.52e-05
pts$hosp_fac1Nearest hospital is less than or equal to 60 min   4.1365e-01  1.6845e+00  0.2456 0.8060183
pts$hosp_fac1Nearest hospital is more than 120 min             5.1139e-01  1.9889e+00  0.2571 0.7970835
pts$hosp_fac1Nearest hospital is more than 60 min             -3.4689e-01  1.7906e+00 -0.1937 0.8463864

Rho: 0.050548, LR test value: 4.5242, p-value: 0.033418
Asymptotic standard error: 0.023631
    z-value: 2.1391, p-value: 0.03243
Wald statistic: 4.5756, p-value: 0.03243

Log likelihood: -2210.368 for lag model
ML residual variance (sigma squared): 92.754, (sigma: 9.6309)
Number of observations: 600
Number of parameters estimated: 17
AIC: 4454.7, (AIC for lm: 4457.3)
LM test for residual autocorrelation
test value: 6.6225, p-value: 0.01007
```

Table 4

6. Conclusion and findings:

Our study finds that in the context of Bangladesh where a community lives as an effect on vaccination coverage. We demonstrate this based on type of connectivity the community has and other community level variables. Since none of the other distance to health facility variable came significant in any of the models, it implies that community health workers play a more crucial role than formal health facilities established by the government. It means that families rely more on health workers to have their children vaccinated and there needs a better transportation and safe delivery and storage system from thana headquarters for the vaccines to reach safely to the communities located in these hard to reach areas.

7. References

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