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Can results-based financing help reduce wealth-based disparities in maternal and child health outcomes in Zimbabwe?

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Abstract
Results-based financing (RBF) program evaluations in sub-Saharan Africa have concentrated on quantifying the impact of such programs on maternal and child health outcomes, worker satisfaction and quality of care. Very few studies have considered assessing the effectiveness of these programs from a distributive perspective. This study uses nationally representative data from the Zimbabwe demographic and health survey complemented with geographic location data. As a first step, the empirical approach quantifies wealth-related inequalities in selected maternal and child health outcomes using concentration indices at the district level. A standard difference-in-difference model complemented by kernel-based propensity score matching was used to consistently estimate the impact of the RBF program on the equality of maternal and child health outcomes across socioeconomic gradients in Zimbabwe by comparing the changes in concentration indices between 2010 and 2015 in ten districts with RBF and thirty districts without the RBF program for twelve indicators of access to maternal health care and nine indicators of child health outcomes. The results show that the RBF program was associated with greater and significant improvements in equity related to the frequency of prenatal care (four or more prenatal care visits), family planning, overall quality of prenatal care and some components of prenatal care (blood pressure check, iron tablets and tetanus toxoid vaccinations), child full immunizations, and treatment for fever occurring in the two weeks before the survey. The RBF program did not appear to ameliorate wealth-related inequality in terms of child low birth weight, neonatal mortality, stunting, diarrhoea prevalence, treatment for diarrhoea, and fever prevalence when inequalities. A sensitivity check of the estimates indicate that our results are weakly robust to the consideration of absolute measures of inequality (slope index of inequality and the generalized Gini index). From a policy perspective, the results have important implications for public health policies geared towards improving access to maternal and child health care services in developing countries. Our analysis clearly reveals that RBF programs do not necessarily eliminate wealth-related inequality in maternal and child health outcomes in Zimbabwe but are certainly a useful complement to equity-enhancing policies in the country.

JEL classification: I11; I14; I18

Key words: Results-based financing; maternal health care; wealth-related inequality; difference-in-difference; Zimbabwe

1. Introduction

Over the last few years, results-based financing (RBF) schemes have gained considerable support among low- and middle-income countries as essential mechanisms to improving health system functionality and health outcomes of vulnerable groups such as women and their children under the age of five years. Broadly defined, RBF strategies comprise a mix of demand and supply-side incentives that encourage the use of health services as well as reward health service providers for providing quality health services or for enhanced system performance (Eichler & Levine, 2009). The RBF schemes in their numerous forms include performance-based financing, performance-based contracting, vouchers, and output-based financial assistance (Musgrove, 2011). Supporters of RBF programs strongly contend that the initiative is a reform strategy with a potential to positively influence health service provision and subsequently improve health outcomes through increased provider autonomy and good national oversight (Meessen, Soucat, & Sekabaraga, 2011) in low-income countries especially in sub-Saharan Africa (SSA) where such outcomes have lagged behind. Other scholars note the flexibility of the RBF program particularly in adapting to the ever-changing health priorities and the dynamics related to country contexts (Basinga, Mayaka, & Condo, 2011; Soeters, Peerenboom, Mushagalusa, & Kimanuka, 2011). On the other hand, critics of the RBF program cite the lack of empirical evidence regarding its effectiveness, impact on non-incentivised health services as well as on its ability to address unjustifiable disparities in health (Priedeman Skiles, Curtis, Basinga, & Angeles, 2013).

There is ample evidence in low-income countries to suggest that access to health services mostly favours individuals living in families of high socioeconomic status (see e.g. Creanga, Gillespie, Karklins, and Tsui (2011); (Gage, 2007; Houweling, Ronsmans, Campbell, & Kunst, 2007; M. Makate & Makate, 2017)). Low-income families are not only constrained financially but, are also less knowledgeable about the benefits of and value of health services (Priedeman Skiles et al., 2013). In low-income countries, the existence of user fees within the health system is often cited amongst the largest barriers to accessing health services (Dzakpasu, Powell-Jackson, & Campbell, 2014). One of the provisions in the RBF program is the removal of user fees associated with access to health services. Thus, it is reasonable to not only assess whether the introduction of the RBF program has impacted access to health services and health outcomes, but also to ascertain the extent to which the program has narrowed the gap between the rich and the poor (this is the distributional effect of RBF exploring its potential impact on socioeconomic status-related disparities in access to health services).

The primary goal of this study is to examine the impact of the RBF program on inequality of selected maternal and child health outcomes and access across the socioeconomic status (as measured by household wealth) gradient in rural Zimbabwe, through a comparison of the changes in inequalities in health outcomes between 2010 and 2015 in 12 districts with RBF and 30 districts without the RBF program. The empirical strategy adopts a quasi-experimental strategy (in difference-in-differences) complemented by kernel propensity matching to minimise the prospect of selectivity bias and uses data from multiple sources including the Zimbabwe demographic and health survey (ZDHS) data, Zimbabwe DHS geographical datasets and from the Global Administrative Areas. Despite making good progress in terms of access to maternal and child health services in the last few decades, previous empirical research suggests that socioeconomic status-driven inequalities in maternal and child health outcomes have risen in Zimbabwe between 1994 and 2011 (M. Makate & Makate, 2017). Zimbabwe's levels of poverty are amongst the worst in the African region, with an estimated 70.5% and 29.3% of the population believed to be in general poverty and extreme poverty, respectively (ZimVAC, 2020). The number of households classified as poor is projected to rise by an estimated 300,000 per year given the projected economic growth rates with vulnerable groups such as pregnant women and children expected to bear the larger burden. Moreover, maternal and child health outcomes remain unsatisfactory in the country when compared to other countries in the African region and globally (World Health Organization, 2020). The succeeding Figures (1) and (2) give an overview of selected maternal and child health outcomes for Zimbabwe relative to just a few countries (arbitrarily chosen) including the averages for the African region and globally.

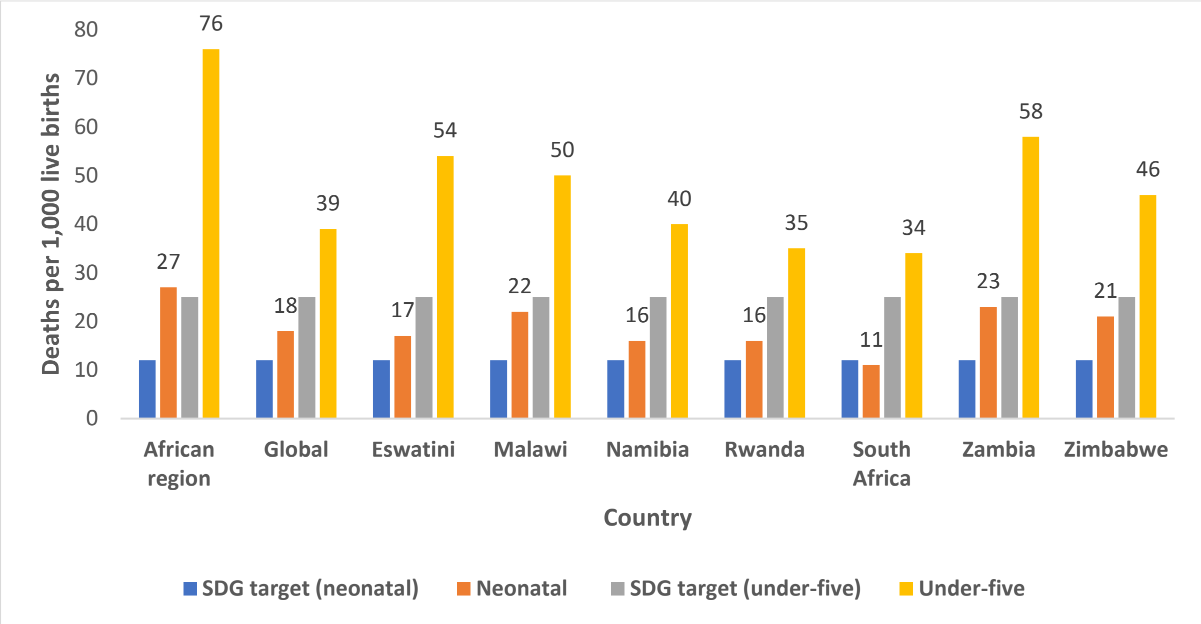

Figure 1. Distribution of average neonatal and under-five mortality (expressed as number of deaths per 1,000 live births) for selected countries in Africa, the African region and globally for the year 2018. Data are sourced from the World health statistics report, 2020 but graphs were drawn by the authors.

Figure 1 shows that average neonatal and under-five mortality rates for the African region, global and selected countries in Africa for the year 2018. For each mortality indicator, we included a sustainable development goals target (=12 for neonatal mortality; =25 for under-five mortality). Among the countries shown in Figure 1, only South Africa has met its neonatal mortality target while other countries still gravitating towards the required target for neonatal mortality of 12 deaths per 1,000 live births by the year 2030. While Zimbabwe is yet to meet both its neonatal and under-five mortality targets, Figure shows that the country is making some good progress when compared to other countries in Africa and the African region as a whole. For example, the neonatal mortality rate for the country in 2018 was 21 deaths per 1,000 live births compared to 27 deaths per 1,000 live births for the African region (46 under-five deaths (Zimbabwe) vs 76 under-five deaths (African region)). Despite the noted progress, the mortality rates for children remain unsatisfactory.

In Figure 2, we show the average distribution of child stunting and skilled delivery assistance for the period 2010-2019. The data shows that an estimated 23.5% of Zimbabwean children aged five years and younger are still considered stunted. Stunting is a condition of impaired growth and development that children experience as a result of inadequate or poor nutrition, repeated infection, and inadequate psychosocial stimulation (World Health Organisation, 2020). Linear growth in early life is an important marker of growth and development in later life. While the average stunting rate for Zimbabwe is lower than the African regional average, it is still relatively high and could be lower. The average skilled delivery assistance (86%) for Zimbabwe is well above the recommended target of 70% but appears to be lower when compared to other countries such as Rwanda (91%) and Malawi (90%).

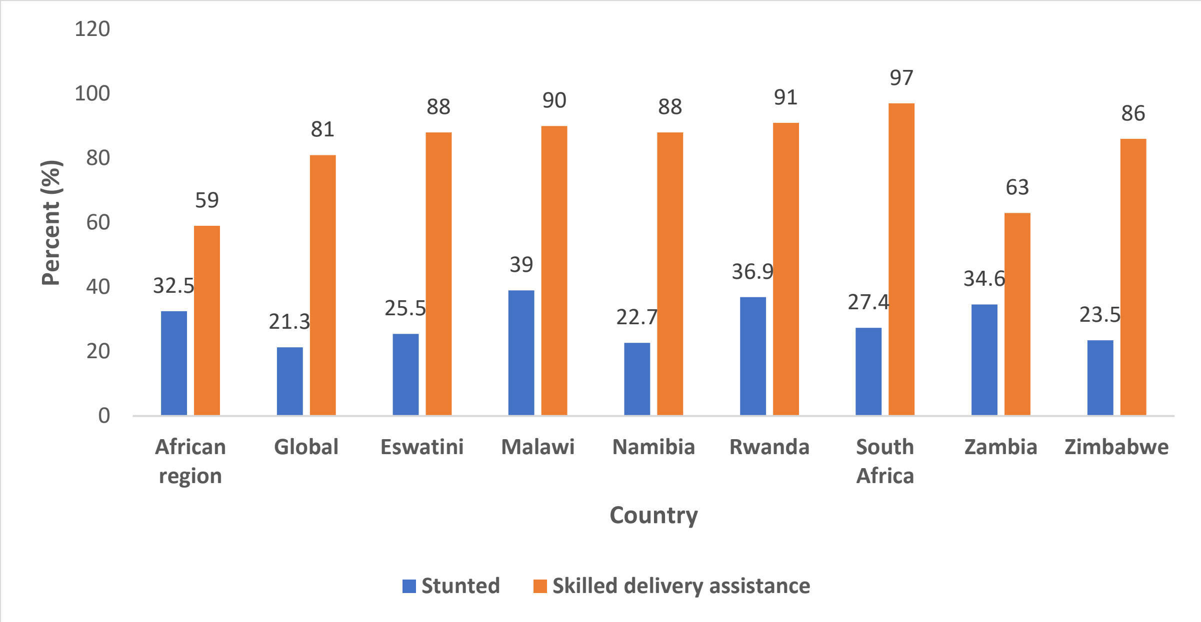

Figure 2. Distribution of average child stunting and skilled delivery assistance for selected countries in Africa, the African region and globally for the period 2010-2019. Data sourced from the World health statistics report, 2020. Data are sourced from the World health statistics report, 2020 but graphs were drawn by the authors.

The statistics presented in Figures (2) and (3) seem to suggest that Zimbabwe is doing reasonably well when compared to other countries of almost similar levels of development. However, what we cannot deduce from these numbers is whether the distribution is comparable among different socioeconomic status groups. Thus, our novel contribution to the literature is to examine whether the introduction of the RBF program in the country has changed the distribution socioeconomic status driven differences in access to maternal and child health services.

2. Literature review

There is ample evidence in low-income countries to suggest that access to health services especially maternal and child health mostly favours individuals from relatively rich or wealth families (i.e. pro-rich) (see e.g. (Creanga et al., 2011; Gage, 2007; Houweling et al., 2007; M. Makate & Makate, 2017; Zeng, Lannes, & Mutasa, 2018)). The existence of user fees associated with access to health care services is amongst the factors limiting increased use of health care services in low-income countries (Dzakpasu et al., 2014). Results based financing (RBF) programs were introduced as a health system strengthening mechanism to not only enhance the quality and quantity of maternal and child health services provided, but also to increase efficiency, equity, and accountability within the wider health care system (World Bank, 2013). Empirical evidence on the evaluation of RBF programs in low-and middle-income countries is relatively scarce. Moreover, the limited available evidence offers mixed results regarding the impact of such programs on health outcomes (Witter, Fretheim, Kessy, & Lindahl, 2012).

Witter and colleagues conducted a systematic search of the literature to document the impact of RBF on health delivery services in low-and middle-income countries. Their review identified nine articles meeting their inclusion criteria and comprised of studies conducted for Vietnam, China, Uganda, Rwanda, Tanzania, Democratic Republic of Congo (DRC) and Philippines. The results showed that the effect of RBF on health service delivery was highly uncertain. Specifically, the authors noted that the impact on coverage of tetanus vaccinations among pregnant women was inconclusive with only one study showing a modest impact of the policy on tuberculosis case detection (Witter et al., 2012). Similarly, the impact on utilisation of antenatal care services, institutional deliveries, and on preventive care services for children including vaccinations also yielded mixed findings. In other research conducted in Burundi, Haiti, Zambia, Cambodia and the DRC, findings from both experimental and quasi-experimental evidence indicate the potential for RBF to improve outcomes related to health service use and financial management capabilities (Chansa et al., 2020; Falisse, Meessen, Ndayishimiye, & Bossuyt, 2012; Matsuoka, Obara, Nagai, Murakami, & Chan Lon, 2014; Meessen, Kashala, & Musango, 2007; Meessen, Musango, Kashala, & Lemlin, 2006; Soeters, Habineza, & Peerenboom, 2006; Soeters et al., 2011; Zeng, Cros, Wright, & Shepard, 2013). Implementation of the RBF program has been associated with an increased probability in the use of prenatal care in DRC and Cambodia (Matsuoka et al., 2014; Soeters et al., 2011). In Chad, the programme was implemented between October 2011 and May 2013 and showed promising signs of impact on the health system. However, it failed to make it through the national policy agenda and was subsequently abandoned due to inadequate or lack of committed policy practitioners in the country (Kiendrébéogo et al., 2017).

In Rwanda, Basinga, Gertler, et al. (2011) examined the impact of RBF on use and quality of child and maternal health care services. Their results showed that the policy was associated with a 23% increase in institutional deliveries, 56% increase in preventive care visits by children aged 23 months and younger (132% increase among children aged 24-59 months), 0.157 standard deviation increase in prenatal quality but no improvements were observed concerning the frequency of prenatal care and full immunization schedules for children (Basinga, Gertler, et al., 2011). In Malawi, Brenner et al. (2018) assessed the impact of the RBF program on effective coverage of facility-based obstetric care services. Their results did not show an effect on crude coverage but rather found an impact on effective coverage of facility-based obstetric care (Brenner et al., 2018). However, the authors highlighted the need for further research assessing the impact of the program over a longer time period (Brenner et al., 2018). In another study for Malawi, De Allegri et al. (2019) used a controlled interrupted time series methodology and found that the RBF programme was associated with a reduction in facility-based maternal mortality.

In Zimbabwe, recent evidence has linked the implementation of the RBF program to improvements in the quality of prenatal care and client satisfaction about the program (Das, 2017). Furthermore, the World Bank conducted an evaluation of the RBF program in Zimbabwe on several maternal and child health outcomes. The study relied on a purposive sampling strategy to select 16 comparison districts based on several characteristics including remoteness, type of constituent facilities, sociodemographic, and rates of health care utilisation (World Bank, 2016). The study used a quasi-experimental design in difference-in-differences analysis to compare changes in selected maternal and child health outcomes between baseline and follow-up periods in both RBF (n=16) vs non-RBF (n=16) districts. The results showed that implementation of the RBF program in Zimbabwe was associated with faster improvements in delivery outcomes (delivery by health professional, facility delivery and delivery by C-section), coverage of postpartum care, antenatal care, and health worker satisfaction among others in RBF districts as compared with non-RBF districts (World Bank, 2016). Additionally, the analysis showed that the program was associated with improvements in child health outcomes and health seeking behaviour for children. Specifically, the program was associated with a decreased probability that a child will have a fever in the two weeks before the survey, decreased prospect of having a height-for-age and weight-for-age z-scores that were below three standard deviation when compared with the reference population of healthy children (World Bank, 2016). While the program was associated with a positive impact on the quality of care, the impact on several components or aspects of the quality of care was rather mixed and inconclusive. In a recent study for Zimbabwe, Das (2017) showed that the RBF was associated with significant improvements in the quality of antenatal care. While the evidence concerning the impact of the RBF program on key maternal and child health outcomes is growing for

Zimbabwe and other low-income countries, we know nothing about the impact of the RBF program on equality of health outcomes and access across the socioeconomic gradient in Zimbabwe.

Our analysis builds from the previous literature in low-and middle-income countries including Zimbabwe to examine the impact of the RBF program on inequality of selected maternal and child health outcomes and access across the socioeconomic gradient in selected rural districts in Zimbabwe. To the best of our knowledge, this is the first study to explore such issues in the context of a low-income country such as Zimbabwe.

3. Overview of results-based financing program in Zimbabwe

Results based financing programs are not only implemented based on the premise that they will enhance the quality and quantity of maternal and child health services provided, but also that they will enhance efficiency, equity, and accountability within the wider health care system (World Bank, 2013). The RBF program in Zimbabwe was initially launched in July of 2011 in two districts namely, Zishavane and Marondera and later expanded to 16 other districts: Gokwe north, Headlands, Binga, Nkayi, Kariba, Chegutu, Mutare, Chipinge, Mwenezi, Chiredzi, Mutoko, Chikombo, Gweru, Gwanda, Mangwe, and Centenary by March 2012. The 18 districts have a catchment area of 385 health facilities with an estimated population coverage of about 3.5 million people. The RBF program in Zimbabwe received funding from the Health Results Innovation Trust with cofounding from the Ministry of Finance and Economic Development and was implemented by Cordaid – a Dutch international non-governmental organisation. For the purposes of this analysis and as guided by the availability of relevant data, we have included 10 RBF districts and 30 non-RBF districts (see the appendix). At the core of the RBF initiative was a promise to subsidize rural health facilities that met a set of agreed targets (quantities and quality) packaged to serve pregnant women and their children under the age of five for free (World Bank, 2013).

The RBF program in Zimbabwe was rolled out in 18 districts as mentioned earlier, covering all health facilities in these districts and consisted of three main aspects including (a) results-based contracting; (b) management and capacity building; and (c) monitoring of the program. The general structure of the RBF program was the same across districts. The contracting component had three elements to it including payment for verified quantity and quality of delivered health services only as well as giving a remoteness bonus for rural health centres or facilities meeting specified performance benchmarks. There were 16 indicators for which the Ministry of Child Health had identified as priorities and were paid on a one unit basis (World Bank, 2016). The priority indicators considered included the following: outpatient department consultations; first antenatal care visits that occurred within the first 16 weeks; four or more antenatal care visits completed; HIV testing given during antenatal care; antiretroviral drugs given to pregnant women to prevent mother-to-child transmission (PMTCT) of HIV; tetanus toxoid vaccinations; number of syphilis RPR tests; normal birth deliveries; high-risk perinatal referrals; two or more postnatal care visits; family planning (short and long-term methods); intermittent preventive treatment (IPT) of malaria during pregnancy; child immunizations; vitamin A supplementation; growth monitoring for children under age five years; and acute malnutrition cured and discharged children below five years.

District hospitals were also compensated based on five key indicators relating to birth deliveries including: normal birth deliveries; deliveries with complications; caesarean sections; family planning tubal ligations; high risk perinatal referrals and acute malnutrition cured and discharged children below five years. Additionally, facilities received a remoteness bonus which was calculated based on the population density, availability of road infrastructure, public transportation and communication, and distance to the closest referring facility. In addition to linking all payments to results the RBF program was also built around five other crucial elements including a segregation of functions between the service provider, purchaser and the regulator. Contracting was not only done with health facilities but also with other stakeholders including district and provincial health executives. The program also recognised the need for decentralising all the planning and health decision making around investments at the health facility level. Furthermore, health facilities in RBF districts and in close consultation with the health centre committees had the power to exercise autonomy to use any proceeds they had received through the program. An estimated 25% of the total proceeds from RBF activities was allowed to be re-invested at the facility level in order to maintain and enhance the physical infrastructure.

One of the elements of the RBF program included in-built measures to address inequality of outcomes. To achieve equity, the program ensured that all user fees at the primary level including in selected secondary level facilities were removed in all intervention districts. Also, health facilities that were not easily accessible (i.e. in very remote locations) and covering a small population were eligible to receive a remoteness bonus as an additional incentive. The RBF also had an important element that incorporated the community voice or feedback through conducting a series of client tracer and satisfaction surveys. For the RBF program, incentives could be received from either of three ways: (i) quantity bonus, (ii) quality bonus, and (iii) patient satisfaction bonus. Figure 3, adapted from the RBF implementation manual in Zimbabwe summarises the general incentive structure of the program.

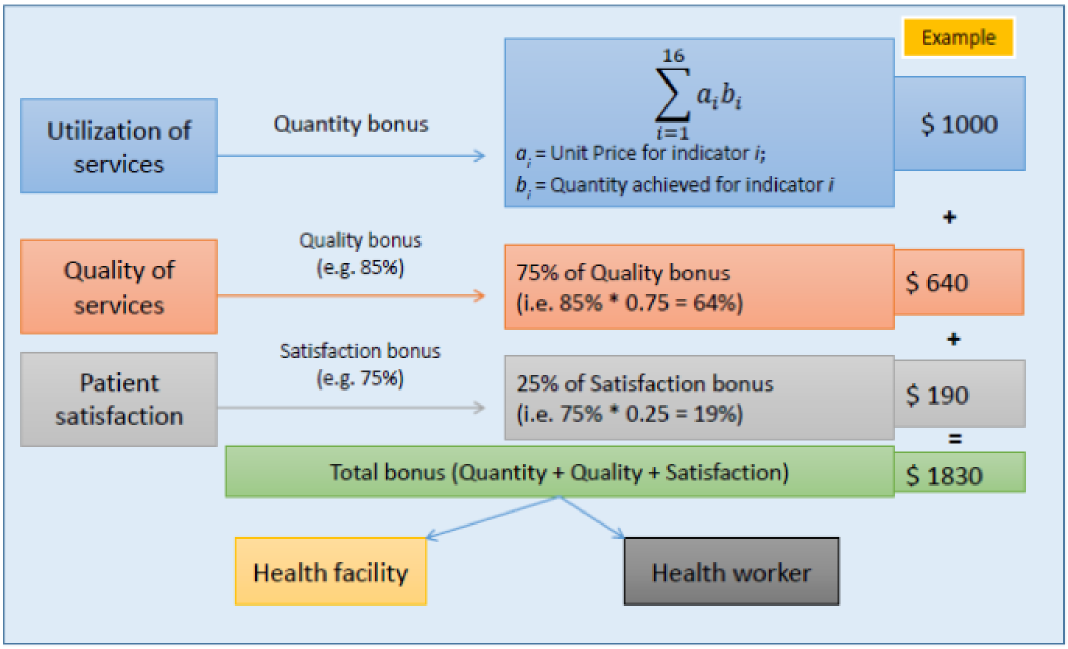

Figure 3. The RBF program's incentive calculation mechanism in Zimbabwe. Figure was sourced from the RBF Project implementation manual in Zimbabwe (Zimbabwe Ministry of Health and Child Care, 2016).

Issues around the management and capacity building were primarily put in place to target health centre committees, district hospitals, steering committees at the district level (World Bank, 2016). Several opportunities for capacity building targeting improved data quality and sound reporting, financial management and procurement, were organised and involved training by international experts in different disciplines as well as a series of workshops and ongoing implementation reviews.

4. Conceptual framework

Results-based financing programs are expected to impact both the quantity and quality of maternal and child health outcomes through the three-pronged incentive mechanism imbedded within the program relating to the use (quantity aspect), quality and client satisfaction component (Zimbabwe Ministry of Health and Child Care, 2016). In reality, the conversion of inputs to final outputs or results is a complex process involving several factors. In this study, we adopt a conceptual framework that has been adopted in previous work by the World Bank which is based on the RBF model's Theory of Change (World Bank, 2016). Figure 4 summarises the RBF model's theory of change.

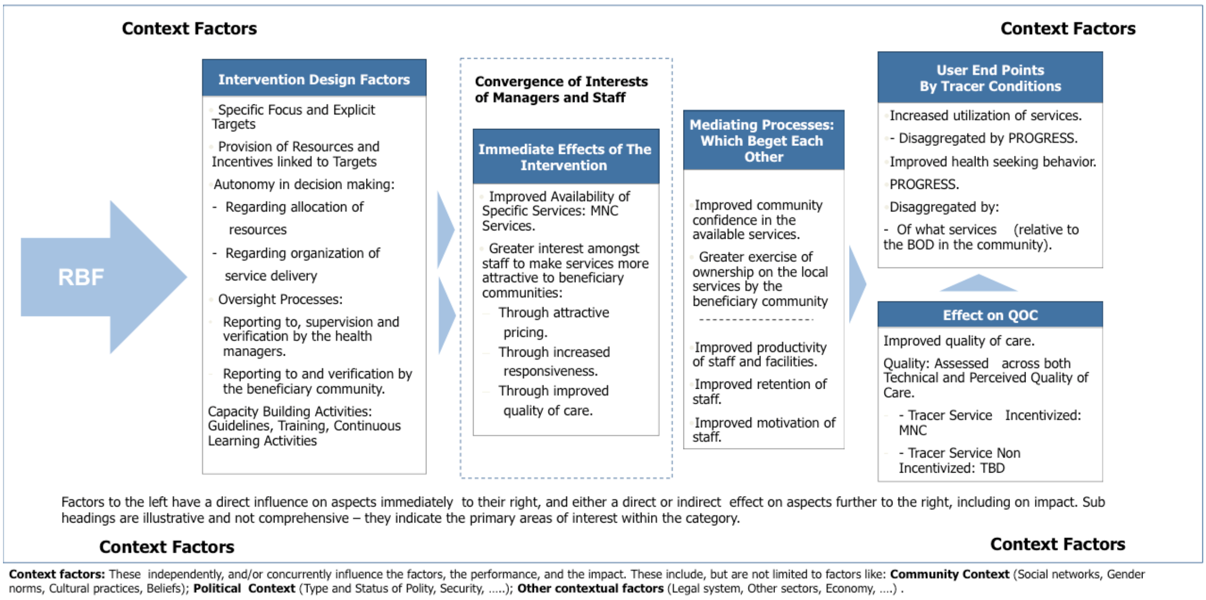

Figure 4. The theory of change RBF in Zimbabwe. This figure was adapted from the World Bank's evaluation report (World Bank, 2016).

According to the theory of change RBF, the achievement of output, health outcomes and effect of the intervention will depend on the interlinkages between the designs of the program, the immediate effects of the policy and the role of contextual and mediating factors. In this instance, the program was designed to effect positive change on maternal and child health outcomes through the different mechanisms or elements imbedded in the program itself e.g. the removal of user fees, capacity building through workshops and training opportunities to staff and several other incentives (World Bank, 2016). The short to medium term impact of these initiatives is to enhance the availability and accessibility of health services to all citizens regardless of socioeconomic status. In health care, the most fundamental concept of equity relates to the notion of horizontal equity – a situation where individuals with similar medical needs are treated the same regardless of their socioeconomic status, location of residence or race among others (O'donnell, Van Doorslaer, Wagstaff, & Lindelow, 2008). Reducing inequalities in health requires a multifaceted approach that involves the achievement of equity in health service delivery (Health, 2008).

The direct impact of the RBF program on equality of health outcomes is rather ambiguous since other contextual factors will likely play a role in this. For example, the community context is likely to impact use of health services in that different communities exhibit different cultural practices, beliefs and norms that are likely to impact the utilisation of health services regardless of the RBF program's provisions. Previous evidence regarding the distributive effect of pay-for-performance programs is limited. However, a systematic review conducted in the context of high-income countries suggested that the impact of RBF programs on health inequalities was ambiguous. In some studies, the study concluded that inequalities in some health outcomes persisted after the introduction of a results-based financing program while in other instances inequalities in health outcomes declined (Alshamsan, Majeed, Ashworth, Car, & Millett, 2010). It is also imperative to note that RBF programs are not the only way to achieve equality of health outcomes and constitute one policy among a set of other social policies that are deliberately designed to address inequalities in access to services. Thus, we expect that the RBF program in Zimbabwe could be associated with a reduction in the level of inequalities among other health outcomes and an increase or no change in inequalities among some health outcomes as well.

5. Data and Methods

5.1 Data sources

5.1.1. Demographic and health survey data

In order for us to assess the distributional impact of the RBF program on maternal and child health outcomes, we rely on microdata from multiple rounds of the Zimbabwe Demographic and Health Survey (ZDHS) – a nationally representative individual household-level dataset collecting health-related information from women aged 15-49 years together with their children born in the five years preceding each survey. The ZDHS is a cross-sectional survey conducted every five years and has been collected in Zimbabwe since 1988. We use four rounds of the ZDHS collected in 1999, 2005/06, 2010/11, and 2015 and for which geographic datasets are available (ZIMSTAT, 2012). Geographic datasets collected by DHS is used in this study as it facilitates with the identification of districts – which are not included as part of the standard DHS data files for Zimbabwe. The ZDHS adopts a two-stage cluster design grounded in the Zimbabwe national population census as the sampling frame (ZIMSTAT, 2016). Basic demographics and health indicators including fertility, contraceptive usage, early childhood mortality, maternal and child health and other behavioural outcomes are all collected. The ZDHS is increasingly becoming an excellent source for reliable and comparable cross-sectional survey data in low- middle-income countries. We use this data as it provides nationally representative and comprehensive health data for women of reproductive ages 15-49 years and their children born in the five years preceding the survey. This survey allows us to text the equity impacts of RBF on several maternal and child health outcomes.

Given that part of the analysis focuses on examining the equity impacts of the RBF program on selected maternal health outcomes, we collect maternal-related information from the DHS individual recodes (i.e. the "IR" DHS recode files). These datasets contain basic background variables such as age, education of women, household wealth, religion, location of residence and health utilisation information such as prenatal care use, contraceptive usage among others. We also collected data on children from the birth history files (i.e. the "BR" DHS recode files). This dataset contains information about the gender, birth order, mortality, anthropometrics and health utilisation data for children born in the five years preceding each survey. In early DHS surveys such as that collected in 1999, other data such as the household wealth index and child anthropometric data are in separate data files. For this survey, we also used the household member recode file, wealth recode file and the file containing the anthropometric data in order for us to collect the relevant data for the analysis that is also available in the most recent surveys.

5.1.2. DHS Geographic data

In addition to the individual-level data, the ZDHS also captures the GPS coordinates (centroid of each cluster) of every primary sampling unit or cluster of households surveyed. The geographic data for Zimbabwe is available for the four most recent surveys. Thus, we are able to collect the GPS data for the 1999, 2005/06, 2010/11 and 2015 DHS surveys. The purpose for collecting the GPS data is for us to identify all the districts – the level of implementation or rollout of the RBF program in Zimbabwe. These data files contain the cluster number or identifier, DHS survey year, latitude and longitude information, region or province name and number, and an indicator for location (urban or rural). The DHS does not record the exact name and location of each primary sampling unit in order to preserve the confidentiality of data for surveyed participants. As such, the GPS coordinates supplied by ZDHS incorporate a random displacement process in which urban primary sampling units were uniformly displaced to a distance measuring two kilometres, rural clusters displaced up to five kilometres with 1% of the clusters displaced to a distance of 10 kilometres (Burgert, Colston, Roy, & Zachary, 2013). The good news is that this displacement is conducted such that clusters are restricted to their second administrative geographic unit (i.e. the district). Despite the introduction of a random error as a result of the displacement process, we strongly believe that this generated random error is highly unlikely to impact our final results and conclusions. Note that, with this geographic data, we are still unable to identify districts in Zimbabwe. Thus, we require yet another dataset.

5.1.3. Health facility data

To complement the main DHS data, we also rely on health facility data sourced from the World Health Organisation (WHO) website (Maina et al., 2019). This data contains a comprehensive list of all health facilities in each country in SSA including the geolocations. We use this datasets to create additional variables measuring the density of health facilities by district and or province. We also created variables measuring the proximity of health facilities to each cluster including the number of health facility within a given radius (e.g. 10, 15, or 20 kilometre radius) away from the centre of each cluster.

5.1.4. Global Administrative Areas Data

The standard DHS data for Zimbabwe does not include information on the second administrative units (i.e. districts). For us to incorporate district information in this dataset, we rely on geographic data from the Global Administrative Areas (GADM) for Zimbabwe (Global Administrative Areas, 2020). The GADM dataset maps the administrative areas such as provinces and districts of several countries, at all levels of sub-division using a high spatial resolution. GADM describes where these administrative areas are (i.e. the spatial features) and for each area the dataset provides the name and variant name of the spatial features. The data is available as shapefile, ESRI geodatabase, RData, and Google Earth kmz formats. For the purpose of this analysis, we collected the shapefile identifying administrative level 2 units (districts) for Zimbabwe. This data is freely available for academic use and other non-commercial use and can be downloaded here https://gadm.org/data.html.

5.1.5. Data management and processing

As a first step, we match the DHS individual and birth recode files by case identifier (a unique mother identifier) and cluster number for each DHS year available. We then append these datasets to create a pooled cross-sectional dataset with women and children information. Since child-level data of interest such as prenatal care, birth weight and anthropometric information among others, are only available for the most recent birth that occurred in the five years preceding the survey, we have one record for every woman surveyed. In this instance, the number of children equals the number of women or mothers hence, questions regarding the unit of analysis become irrelevant in this instance.

We process the geographic data separately from the main household-level dataset described earlier. To start with, we use ArcMap version 10.4 computer software to import the shapefile data containing the administrative level 2 data collected from GADM. Then, for each DHS year, we map or link DHS clusters to their respective districts. This process is followed by a manual process in which we systematically extract cluster numbers for each district and create an excel data file for each DHS year. In each excel file, we capture the cluster number (exactly as it appears in the DHS survey datasets), the survey year, province name and number (exactly as these appear in the DHS data), urban or rural indicator. We then append all the created excel data files. In essence, we have created a panel dataset at the district level in which some and not all districts will have information for the years 1999, 2005, 2010 and 2015. We follow exactly the same process in creating a data file containing health facility information.

The next step in the data management and processing is straightforward as it involves matching or merging the pooled geographic dataset to the pooled individual household-level DHS data. In order to complete this last step, we matched the two data files using the following as keys to the “one-to-many” merge: cluster number and survey year. We only used the two keys to the merge since DHS clusters are unique in each survey year. In other words, in a particular DHS year, it is not possible to have two clusters with the same number.

In the next step, we proceeded to create a dataset comprising of the same number of districts before and after the intervention. Specifically, we created a dataset such that a district was available in both the 2010 (baseline data before RBF program) and 2015 (post program data) datasets and that the district had at least 20 observations of data for any of the health outcomes of interest. After dropping other districts with observations below the 20 threshold, and that did not appear in either survey ear, we are left with 42 districts out of the possible 60. For the main analysis dataset, we have a total of 12 RBF districts contributing 5,857 observations and 30 non-RBF districts contributing 19,987 observations.

5.2 Household wealth as a measure of socioeconomic status

Our measure of socioeconomic status is an asset-based wealth index constructed using Principal Components Analysis (PCA). Several studies in low-income nations have used the household asset index computed via PCA as the principal measure of socioeconomic status (M. Makate & Makate, 2017; O'donnell, Van Doorslaer, Wagstaff, & Lindelow, 2007). In this study, we are not calculating the household wealth index as it comes pre-calculated by the ZDHS. Using household wealth as a measure of socioeconomic status comes with several advantages including the fact that wealth represents a more permanent status as opposed to other measures such as consumption or income (Rutstein, 2008). Since information on income and / or consumption – the typically used measures of socioeconomic status are difficult and even expensive to measure in low-income countries where informal markets predominate, the asset-based index is the usually preferred alternative (O'donnell et al., 2007).

The DHS uses several variables in the computation of household wealth index. These variables relate to the ownership of assets, services and several other things belonging to each household included in the survey. The assets included in the calculation of the index range from ownership of radios, television, telephone, refrigerator, vehicles, bicycles, livestock to agricultural land. Also included in the calculation of this index are housing characteristics including source of drinking water, sanitation infrastructure, household construction material, electricity, number of people per sleeping room, having domestic servants and several others.

The asset index is calculated using PCA – a multivariate statistical technique that is widely used as a data reduction method. This technique creates uncorrelated components with each component comprising of a linear weighted combination of the original asset variables. The resulting components are arranged in such a way that the first principal component explains the largest variability in the data. This principal component is the continuous score (continuous variable) that is used to rank all the individual households in the calculation of inequalities (hence, wealth-related inequalities). A further categorisation of the households into five household wealth quintiles ranging from the poorest (household wealth quintile 1) to the richest (household wealth quintile 5) was also made.

5.3 Study variables of interest

This study purposes to examine the distributional impact of RBF program on maternal and child health outcomes in Zimbabwe. We use several variables as measures for maternal health and child health.

Maternal health measures: We rely on several variables as measures of maternal health utilisation. These variables are often used in the empirical literature with many of which were amongst the primary targeted outcomes by the RBF program. First, we created several measures to measure prenatal care utilisation in terms of its frequency and timing. For this, we created two dummy indicators that equal one if (i) each woman completed four or more prenatal visits during her most recent pregnancy and zero otherwise and (ii) if prenatal care was initiated in the first three months of pregnancy (first trimester) and zero otherwise.

Second, we considered the quality of prenatal care including the specific contents received during pregnancy. Following M. Makate and Makate (2016), we created an additive index to measure prenatal care quality. This index is a summation of the number of prenatal care services that each woman received during her most recent pregnancy which included the following: blood pressure check, urine same test, blood sample check, iron tablets and tetanus toxoid vaccinations. If the woman indicated to have had received any of the mentioned components of prenatal care, we coded that with a one and zero otherwise.

Third, we created dummy variables equalling one if the woman had delivered her baby in a health facility (e.g. clinic or hospital or not and zero otherwise. We also included a dummy indicator that took one if the woman had received assistance from a qualified health professional (such as a doctor or nurse) during the delivery of her baby and zero otherwise. Also, we created a binary variable that equals one if the woman had a C-section delivery and zero otherwise. Lastly, we created a dummy variable that equalled one if the woman reported to have been using any of the modern contraceptive methods (family planning) and zero otherwise.

Child health measures: We created several variables as measures of child health outcomes or health service utilisation. We created a dummy variable that took one if a child had received postnatal check-up within the two months after birth and zero otherwise. Also, we constructed a dummy variable measuring whether children had received all the recommended schedule of vaccines such as BCG vaccines for tuberculosis, polio (all the three doses), diphtheria (all three doses), tetanus (all three doses), pertussis (all three doses), and the measles vaccine. A dummy indicator variable for weight at birth less than 2500 grams was also created as a measure of low birth weight. A dummy indicator equalling one if a child had died before celebrating their first month of birth (neonatal mortality) and zero otherwise was also created. Child stunting was measured as a dummy variable that equalled one if the child's height-for-age z-score was below minus two standard deviation of the reference population and zero otherwise. Lastly, we created four other dummy variables measuring the probability that in the two weeks before the survey, a child had fallen sick from diarrhoea, fever and never received treatment for the diarrhoea and fever.

5.4 Empirical strategy

The empirical analysis proceeds in two steps. First, we quantify wealth-related inequalities in several maternal and child health outcomes for each district and by survey year following a standard methodology adopted in previous studies in health economics (see for example, (Kakwani, Wagstaff, & Van Doorslaer, 1997; M. Makate & Makate, 2017; O'donnell et al., 2007; Wagstaff, Paci, & Van Doorslaer, 1991)). The economics literature provides several ways to measure inequalities in health some of which include the Gini coefficient, relative index of inequality, relative index of dissimilarity and the concentration index (O'donnell et al., 2007). We follow the health economics literature that mostly uses concentration indices to measure and quantify wealth-related inequalities in health outcomes (Wagstaff et al., 1991). As suggested by Wagstaff et al. (1991), a robust index measuring wealth-related inequality ought to fulfil at the very minimum the following conditions: (i) a reflection of the disparities in health springing from the socioeconomic characteristics; (ii) it should to be archetypal of the overall respective populace; and (iii) this index should be responsive to any changes in the underlying distribution of the populace across numerous socioeconomic sections. Our choice for the concentration index as the principal measure of wealth-related inequalities in maternal and child health outcomes is primarily driven by the noted deficiencies of commonly used indices such as the Gini coefficient which fails to fulfil the first criteria mentioned earlier (Wagstaff et al., 1991). The concentration index approach entails the plotting of the numbered population of individuals, ranked in ascending order of the socioeconomic status variable, typically income, against the cumulative percentage of the health outcome variable of interest. Following Kakwani et al. (1997), the concentration index $CI(h_i)$ can be calculated using the succeeding "convenient" regression specified as follows:

$$2\sigma_r^2\left(\frac{h_i}{\mu}\right) = \alpha + \beta r_i + \varepsilon_i \qquad (1)$$

where σ_r^2 measures the variance of the fractional rank, μ represents the overall average outcome variable for the whole population, h_i is our outcome variables of interest measuring either maternal or child health, $r_i = i/N$ denotes the fractional rank of the i^{th} individual in the wealth distribution with $i = 1$ representing the lowly ranked individual and $i = N$ representing the highly-ranked individual in the wealth distribution. Estimating equation (1) through ordinary least squares (OLS) gives us the estimate, β, which is the concentration index (O'donnell et al., 2007) with autocorrelation-corrected standard errors (Newey & West, 1994). The $CI(h_i)$ index is bounded between the values $(CI(h_i) = [-1,\ 1])$ with -1 suggesting a pro-poor concentration of the health outcomes, zero denoting the absence of inequalities, and $+1$ reflecting a concentration of health outcomes in the relatively affluent group of the population (O'donnell et al., 2007).

As noted in Adam Wagstaff (2005), instances when the outcome variable is binary, the computed C index may not necessarily be confined to the -1 and $+1$ bounds and that the index may violate other essential properties of an index of disparity such as the "mirror property" (Clarke, Gerdtham, Johannesson, Bingefors, & Smith, 2002; Erreygers, Clarke, & Van Ourti, 2012). Thus, we use the Erreygers (2009) corrected form of the $CI(h_i)$ index which is algebraically specified as follows:

$$E(h_i) = \frac{4\bar{h}}{(h^{max} - h^{min})} \times CI(h_i) \qquad (2)$$

where $\bar{h}$ denotes the mean of the outcome variable of interest, h^{min} and h^{max} are the lower and upper extremes of the outcome variable of interest, and $CI(h_i)$ is as mentioned earlier. In our case, equation (2) reduces to the following:

$$E(h_i) = 4\bar{h} \times CI(h_i) \qquad (3)$$

In the second step of the empirical analysis, we examined the impact of the RBF program on inequality of maternal and child health outcomes and access across socioeconomic gradients in Zimbabwe using a difference-in-differences (DD) methodology. In this approach, we compare the changes in concentration indices between 2010 and 2015 in 12 districts with and 30 districts without RBF for several indicators of maternal and child health. The DD approach is combined with matching to minimise potential differences across districts due to observable characteristics. Our analysis model, based on a DD estimator takes the following basic formulation:

$$HI_{it} = \beta_0 + \beta_1 RBF_i + \beta_2 post_t + \beta_3 RBF_i \times post_t + \delta' X_{it} + u_{it} \qquad (4)$$

where HI_{it} – the dependent variable, represents wealth-related inequality in selected maternal and child health outcomes derived using the variables described earlier. On the right hand side of equation (4), the model incorporates an indicator for whether the district was part of a results-based financing program or not (RBF_i); an indicator for the post policy implementation period ($post_t$); interaction term between the treatment indicator and the post policy implementation indicator ($RBF_i \times post_t$); a vector of observable characteristics (X_{it}) measured at both the individual and district levels; and an error term u_{it}. The RBF program started in 2011 in two districts namely Marondera and Zvishavane but later expanded to 16 other districts in 2012. In this study, we rely on data from 12 of the 18 RBF districts and 30 out of the 42 non-RBF districts. A complete listing of these districts is provided as an appendix (see appendix Table A5). Our analysis considers data from the 2010 and 2015 ZDHS as the baseline and follow-up survey data, respectively.

The effect of the RBF program we seek to estimate can be interpreted as a measure of the intent-to-treat (ITT) effect as we do not necessarily know whether the targeted women (mostly pregnant women) in the RBF districts actually benefited from the program or not – hence, intention-to-treat.

However, since exposure to, or take up to the program was voluntary, selection bias emanating from unobservable characteristics between exposed and non-exposed individuals is probable. To minimise the potential biases associated with selection bias, we combine difference-in-difference method with kernel propensity score matching (henceforth, PSMDD). The advantage of this approach is that we are able to net-out selection on observed and unobserved differences that exhibit no variation over time (Imbens, 2004). The PSMDD method compares the maternal health outcomes before and after the policy implementation to those of the comparison group before and after the policy intervention. This estimator can be represented using the following expression:

$$ITT = E\left(HI_{i,post}^{T} - HI_{i,pre}^{T} | X_i^T, \emptyset_i^T, D_i = 1\right) - E\left(HI_{i,post}^{NT} - HI_{i,pre}^{NT} | X_i^T, \emptyset_i^T, D_i = 1\right) \quad (5)$$

where $HI_{i,post}^{T}$ and $HI_{i,pre}^{T}$ are the treatment and nontreatment health outcomes (concentration indices) in district i before (pre) and after (post) the intervention, respectively; X_i^T is a vector of observable characteristics (individual and district levels) of treatment group; $\emptyset_i^T$ is a vector of unobservable characteristics within district i exposed to the program; D_i is a dummy indicator equals one if individual i belongs to a treatment district and zero otherwise. Here, $(T = 1)$ implies exposure to treatment $(NT = 1 - T)$ means no exposure to treatment. We estimate the DD model with and without additional controls. Given that the second term $E\left(HI_{i,post}^{NT} - HI_{i,pre}^{NT} | X_i^T, \emptyset_i^T, D_i = 1\right)$ in equation (5) is not observed, the standard approach in the matching literature is to assume that exposure to treatment is random only if the treatment and comparison groups are matched on observable characteristics such that $X_i^T = X_i^{NT} = X$ (Rosenbaum & Rubin, 1985). The latter implies that $E\left(HI_i^{NT} | X_i, \emptyset_i^T, D_i = 1\right) = E\left(HI_i^{NT} | X_i, \emptyset_i^{NT}, D_i = 0\right)$. With minimal algebraic manipulations, the ITT estimate can now be formulated as follows:

$$ITT = E\left(HI_{i,post}^{T} - HI_{i,pre}^{T} | X_i, \emptyset_i^T, D_i = 1\right) - E\left(HI_{i,post}^{NT} - HI_{i,pre}^{NT} | X_i, \emptyset_i^{NT}, D_i = 0\right) \quad (6)$$

Assuming the vector $\emptyset_i$ does not vary with time or varies with time but there exists a common trend between the treatment and comparison group. Following Rosenbaum and Rubin (1983), we can estimate the ITT as a function of or conditioning on the propensity score, $p_i = p(D_i = 1 | X_i)$. Incorporating the latter, we can express equation (6) as follows:

$$\begin{aligned} ITT = {} & E\left(HI_{i,post}^{T} - HI_{i,pre}^{T} | p(D_i = 1 | X_i), D_i = 1\right) \\ & - E\left(HI_{i,post}^{NT} - HI_{i,pre}^{NT} | p(D_i = 1 | X_i), D_i = 0\right) \quad (7) \end{aligned}$$

Estimation of equation (7) proceeds as follows: first, we estimate a standard probit model to generate a propensity score – representing the probability that an individual resides in an RBF district taking into account potential sources of observable differences at baseline or before the policy change and represented by vector, X_i. Since the RBF program primarily targeted districts of relatively low socioeconomic status or vulnerable districts with poor health outcomes, we included individual/household-level controls for: number of years of schooling, household size, urban residence, province of residence and province-specific time trends. District-level variables we included as additional controls were: percentage of children under age five who were deceased by the survey date, fraction of women who give birth as teenagers, proportion of women who completed primary school, proportion of women who finished secondary school, share of children aged five years and younger, percentage of uneducated men, fraction of households classified as poorest (household wealth quintile 1), fraction of households classified as richest (household quintile 5), percentage of women who are working, share of women working in agriculture, and the percentage of households headed by females. We also included a variable measuring the number of health facilities within a district. After generating the propensity score using the observed covariates, we restrict analysis to all individuals falling into the region of common support to increase the internal validity of the estimates (Villa, 2016).

For the matching, we rely on a biweight kernel function with the preferred bandwidth based on Silverman's rule of thumb (Silverman, 2018). Each individual in the treatment group is matched to the whole sample of control units rather than just a few select nearest neighbours and all based on the propensity score (Heckman, Ichimura, & Todd, 1998; Heckman, Ichimura, & Todd, 1997). Following Heckman et al. (1997), the propensity score generated from the kernel matching is used to calculate kernel weights which are used to adjust for observed differences at baseline and expressed as follows:

$$w_i = \frac{K\left(\frac{p_i - p_k}{b_n}\right)}{\sum K\left(\frac{p_i - p_k}{b_n}\right)} \qquad (8)$$

where $K(.)$ represents the kernel function and b_n is the selected bandwidth and w_i is the kernel-generated weight for each individual i. Rewriting equation (7) to incorporate the kernel weights results in the kernel propensity-score matching DD treatment effect expressed as follows:

$$ITT = \left\{E\left(HI_{i,post} | D_i = 1, T = 1\right) - w_i \times E\left(HI_{i,post} | D_i = 0, T = 0\right)\right\}$$
$$- \left\{E\left(HI_{i,pre} | D_i = 0, T = 1\right) - w_i \times E\left(HI_{i,pre} | D_i = 0, T = 0\right)\right\} \qquad (9)$$

Given the multiple stages involved in the estimation process, uncertainty in the computed estimates is inevitable. To minimize potential bias due to uncertainty in our estimates, we calculated bootstrapped standard errors with 1000 replications (Freedman & Peters, 1984). We use the Stata user-written command, *diff* to estimate the ITT specified in equation (9) (Villa, 2016). All analysis was conducted using Stata version 15.1.

5.5 Testing the parallel trends assumption

This study uses a DD methodology combined with PSM to examine the impact of the RBF program on inequality of maternal and child health outcomes and access across the socioeconomic gradients in Zimbabwe. The only requirement for identification of the policy impact is that the so called "parallel trends" assumption holds. The parallel trends assumption stipulates that any observed changes in the outcomes in the non-RBF districts represents what would have otherwise occurred in the RBF districts if the program was not rolled out. Thus, any changes in the trends for the outcomes of interest are then ascribed to the implementation of the program itself. In theory, this assumption is by definition not testable since for the RBF districts we are not able to observe the changes in outcomes in the situation with and without the program implementation. However, for a number of the maternal and child health outcomes in this study, we are able to test whether the pre-trends are parallel since we do have data available for several periods before the intervention itself. In essence we are testing the null hypothesis that the pre-trends in outcomes are not statistically significant.

In order for us to provide a formal test of the parallel trends assumption in the RBF and non-RBF districts within the context of a pooled cross-sectional household dataset, we use the following model specification:

$$HI_{it} = a_0 + b'survey + \mu RBF_i + \beta' RBF_i \times survey + \delta' X_i + e_{it} \qquad (10)$$

where $survey$ is a 3×1 vector of time dummy variables representing the survey years 1999, 2005 and 2010; RBF_i is the policy exposure dummy variable as mentioned earlier, HI_{it} measures health inequality in several outcomes as described earlier, X_i is a vector of province fixed effects and e_{it} is an error term. Our interest lies in the vector of coefficients (three coefficients) captured by β'in which we interact the survey year with the dummy variable representing RBF districts. We conduct an F-test to test the hypothesis that the coefficients on the interaction terms are jointly equal to zero. If the coefficients on the interaction terms are jointly equal to zero then, we have confidence to believe that the parallel trends assumption is not violated. We test for parallel trends in both the maternal and child health outcomes of interest. The results for these tests are presented as supplementary material in the appendix. For brevity, we report the coefficients of the interaction terms as described and report the probability values (p-value) for the F-test for joint significance test.

5.6 Robustness checks – measuring inequality using the slope index of inequality (SII)

The concentration index is a measure of relative inequality that indicates the extent to which a health indicator is concentrated among the disadvantaged or the disadvantaged groups of the population (Koolman & Van Doorslaer, 2004). However, measuring inequalities on both relative and absolute scales is now a widely recommended practice in the empirical literature (Ante-Testard et al., 2020; King, Harper, & Young, 2012). This is particularly important in the case when changes in the distribution of inequalities is considered more important, since relying on a relative measure alone could alter or skew research conclusions as well as policy recommendations. Therefore, as a robustness check to our findings, we considered an alternative measure of health inequality, the slope index of inequality (SII) – a widely used measure of absolute inequality in the epidemiology and economics literature (Barros & Victora, 2013; Mackenbach & Kunst, 1997; Moreno-Betancur, Latouche, Menvielle, Kunst, & Rey, 2015). The SII expresses the health inequality between the top and bottom of the socioeconomic status hierarchy in terms of rate differences (Mackenbach & Kunst, 1997). This index is typically computed through linear regression of the health outcome on the midpoints of the ranks obtained by ordering the analytical sample by the independent variable (in this instance, household wealth quintiles) in the case of grouped data (Barros & Victora, 2013). The SII is the slope of the resulting linear regression and measures the absolute difference in the fitted value of the health outcome between the highest (score of one) and the least (score of zero) values of the ranking based on the household wealth indicator. In this study, we regressed the health outcome of interest against the midpoint value using logistic regression (for binary outcomes) in order to calculate the SII (Barros & Victora, 2013).

We also considered measuring absolute health inequality using the generalized Gini index (O'Donnell, O'Neill, Van Ourti, & Walsh, 2016; Wagstaff et al., 1991). The generalized Gini index or generalized concentration index is calculated by multiplying the standard concentration index by the average of the health outcome variable of interest and is used to assess absolute health inequality (O'Donnell et al., 2016). The results for the robustness checks are all presented as supplementary material in the appendix (Tables A6-A13). All analysis was conducted in Stata version 15.1 using the user-written command *siilogit* for SII and *conindex* for concentration indices.

6. Results

6.1 Descriptive statistics

Table 1A provides a summary of the basic selected characteristics among RBF and non-RBF districts in 2010 and 2015. The average years of schooling for women in RBF districts was about 7.2 years before the program compared to 7.91 years in non-RBF districts. We observed a general increase in the years of schooling for women in both RBF and non-RBF districts (i.e. 8.65 vs 8.97 years, respectively). The average household size, birth order, child mortality as observed at survey date, the proportion of teenage mothers, fraction of children who are under the age of five years, and the share of women who are working appears to be similar in both groups before and after the introduction of the policy. The share of individuals from households classified as poorest (wealth quintile 1) appears to be higher in RBF than non-RBF districts both before and after the introduction of the program and vice versa for the case of individuals from households that are classified as richest (wealth quintile 5).

Table 1A: Survey-weighted summary statistics of selected variables by Zimbabwe DHS round and RBF status

		Pre-RBF (ZDHS 2010)		Post-RBF (ZDHS 2015)	
Variables	Full sample	RBF district	non-RBF	RBF district	non-RBF

	(N=25,844)	(N=1,896)	district (N=8,050)	(N=3,961)	district (N=11,937)
Years of schooling (woman)	8.04	7.20	7.91	8.65	8.97
Household size	5.63	5.63	5.55	5.53	5.47
Child's birth order	2.41	2.40	2.36	2.35	2.31
Children deceased by survey date	0.08	0.08	0.08	0.07	0.07
Teenage mothers	0.05	0.05	0.05	0.04	0.05
Women with primary education	0.96	0.89	0.94	0.98	0.98
Women with secondary education	0.52	0.42	0.51	0.55	0.59
Under-five children	0.74	0.71	0.72	0.74	0.73
Uneducated males/partners	0.03	0.09	0.04	0.03	0.01
Household wealth (quintile 1)	0.27	0.32	0.23	0.27	0.18
Household wealth (quintile 5)	0.14	0.15	0.18	0.22	0.24
Employed women	0.42	0.39	0.41	0.46	0.49
women working in agriculture	0.26	0.20	0.19	0.30	0.32
Urban resident	0.20	0.31	0.36	0.38	0.40

Notes: Data is from the 2010 and 2015 Zimbabwe Demographic and Health Survey.

6.2 Propensity score matching results – balancing tests

An important aspect influencing the validity of a DD approach in the context of our analysis is that differences between RBF and non-RBF districts are stable over time and that observed changes in exposure to the policy are not in any way related to changes in the distribution of observed characteristics at baseline. Two criteria must be satisfied for us to have confidence in the PSM results. The first criteria is that there must exist what is called a region of common support of the propensity scores from the sample from RBF vs that from non-RBF districts. The existence of a region of common support translates to the observation that there is a sufficient overlap of efficient matches. The second criteria relates to the quality of the matching. In this instance, a good quality matching process should result in a balance of the pre-policy characteristics for RBF and non-RBF observations. We plot the distribution of the propensity scores from RBF vs non-RBF districts in Figure 1. The results shows that the propensity scores exhibit a good level of overlap such that the first criteria regarding the existence of a region of common support is satisfied.

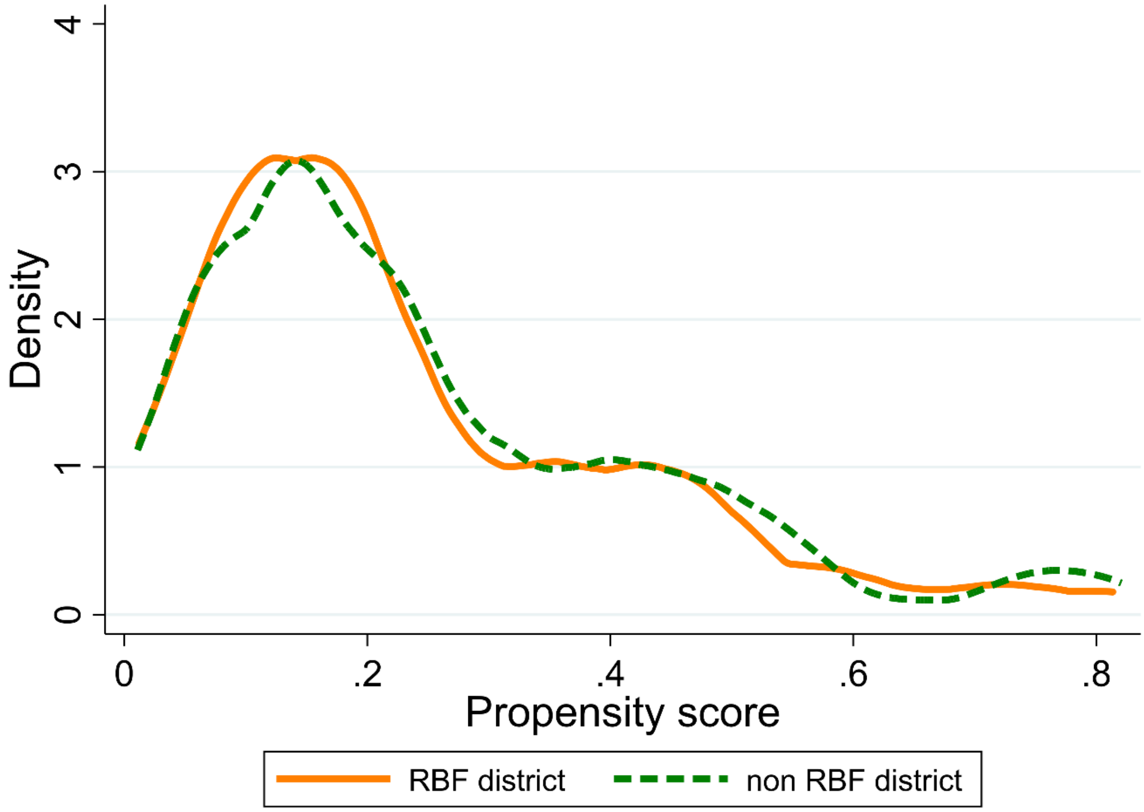

Figure 5. The figure plots the propensity score to gauge the degree of overlap and region of common support between RBF districts and non-RBF districts.

Table 1B reports the balancing test results for all the variables considered for the analysis and based on the kernel matching. The balancing test is conducted for each covariate and using baseline data only (Villa, 2016). The results reported in Table IB are already weighted to show the differences between RBF and non-RBF districts. The results indicate that the balancing test is indeed satisfied and that both individual and district-level covariates are well balanced at the baseline (survey year 2010). The balance in the covariates for the two groups ensures the reliability of our estimations.

Table 1B: Balancing tests from kernel matching (baseline, 2010 data only)

Variables	Mean – non-RBF districts	Mean – RBF districts	Difference	t-value	p-value
Individual-level characteristics					
Years of schooling (woman)	8.209	7.902	-0.307	0.34	0.74
Household size	5.235	5.229	-0.006	0.02	0.99
Child's birth order	2.174	2.296	0.121	0.98	0.33
District-level characteristics					
Children dead by survey date	0.101	0.083	-0.017	1.03	0.312
Teenage mothers	0.047	0.054	0.007	0.84	0.41
Primary education (women)	0.927	0.923	-0.004	0.11	0.92
Secondary education (women)	0.527	0.5	-0.028	0.28	0.78
Under-five children	0.685	0.713	0.029	0.50	0.62
Uneducated males/partners	0.045	0.045	0.000	0.00	0.10

Household wealth (quintile 1)	0.202	0.171	-0.031	0.37	0.71
Household wealth (quintile 5)	0.216	0.199	-0.017	0.15	0.88
Employed women	0.534	0.479	-0.055	0.50	0.62
Women working in agriculture	0.239	0.24	0.002	0.02	0.98
Female head of households	0.428	0.422	-0.005	0.14	0.89
Health facilities (within 60 km of cluster)	46.418	41.971	-4.446	0.36	0.72
Provinces/regions					
Mashonaland central	0.423	0.172	-0.251	1.00	0.32
Mashonaland east	0.051	0.146	0.095	0.81	0.42
Mashonaland west	0.254	0.11	-0.144	0.8	0.43
Matabeleland north	0.053	0.039	-0.014	0.2	0.85
Matabeleland south	0.004	0.022	0.018	0.76	0.45
Midlands	0.07	0.207	0.138	0.81	0.42
Masvingo	0.065	0.179	0.114	0.67	0.51
Number of observations	8050	1896			

6.3 Distribution of concentration curves for RBF vs non-RBF districts

Concentration curves plot the cumulative percentage of the health variable of interest (in this instance, maternal and child health variables) on the vertical axis (y-axis) against the cumulative percentage of the population, ranked by household wealth and starting from the poorest to the richest and represented on the horizontal axis (x-axis) (O'donnell et al., 2008). The 45-degree line – a line that cuts through from the bottom left-hand corner to the top-right hand corner represents the line of equality. A concentration curve will lie above (below) the line of equality if and only if the outcome variable is highly (lowly) concentrated among poor people (Sahn, Younger, & Simler, 2000). The more distant the curve is from the line of equality, the more concentrated the outcome variable is among the poor or vulnerable people. For brevity, we furnish the results for the concentration curves of selected maternal and child health outcomes in the appendix. In all the graphs (Figures 1A-9A), we draw concentration curves for maternal and child health outcomes for RBF districts compared to non-RBF districts and before (2010) and after (2015) the program using household wealth as the measure of socioeconomic status.

Figure 1A shows the concentration curves for the outcome variable representing the receipt of four or more prenatal care visits. In 2010, the concentration curves for RBF and non-RBF districts appear to lie below the 45-degree line for the most part implying that the outcome variable was less concentrated among the poor in 2010 in both districts. Specifically, we noted that the concentration curve for prenatal care falls above the 45-degree line only in the bottom 20% of the women. Following the implementation of the RBF program, the concentration curves for the two districts appear to be as close to each other and to the line of equality suggesting a decline in inequality. Through visual inspection, we are able to observe that no curve dominates the other since the two curves do cross each other at several points some points. It appears that the level of inequality regarding receipt of four or more prenatal care visits show some improvements in the period after the passage of the RBF program. In Figure A2, we visualise the concentration curves for the maternal outcome variable relating to the use of modern contraception methods. It is evident that prior to RBF, use of modern contraceptive methods was highly concentrated among wealthier households. In the period after the RBF, we observe that the concentration curve for the RBF districts move closer towards the 45-degree line and appears to match that of non-RBD districts. This suggests that after RBF, the relatively poor individuals now have better access to modern contraceptive methods. Figures A3-A5 show the distribution of the concentration curves for three components for the content of prenatal care. The graphs show that these outcomes are less concentrated among the poor but, seem to show an improvement in equity following the RBF program.

Figure A6 shows the concentration curves for the outcome relating to delivery in a health facility. The concentration curves for both groups lie everywhere below the line of equality implying that delivery in a health facility is highly concentrated among the richer women (i.e. less concentrated among the poor women). The concentration curves in 2010 (before RBF) appear to be further away from the line of equality – indicating higher degree of inequality and to the advantage of women from relatively wealthy households. Looking at the distribution of the curves in 2015, it is evident that the degree of inequality improved to a certain extent as shown by the shrinking area between the concentration curves and the line of equality. It appears that poor women have better access to delivery care in a health facility in both RBF and non-RBF districts. The same can also be said in Figure A7 regarding skilled delivery assistance. Figure A8 shows the concentration curves for outcomes relating to child full immunization. Figure A8 shows that for 40% of the women, the concentration curve for RBF districts lies below the 45-degree line indicating that child full vaccinations were less concentrated among the poor in the period before RBF in 2010. In 2015, the distribution shows that the two curves lie very close to each other, below the line of equality and showing a decline in inequality in the period after RBF. In Figure A9, the concentration curve for RBF districts appear to be above the line of equality only in the bottom 45% of the women in the period after RBF policy but appears to wander away from the line of equality for the top 55% of women. Overall, it appears that neither of the concentration curves for the two groups dominate each other since both curves do cross each other at numerous points for all our outcome variables. Regardless of the lack of dominance, our analysis does show that while the RBF program in Zimbabwe did not eliminate wealth-related inequality in maternal and child health outcomes, the program could be a useful complement to the set of policies specifically designed to address inequalities in access to maternal and child health outcomes.

6.4 Distributional impact of RBF on wealth-related inequalities in maternal health outcomes

Table 2 presents the results exploring the impact of the RBF program on inequality of selected maternal health care outcomes and access across socioeconomic gradients in Zimbabwe. In this instance, we compare the changes in concentration indices (expressed as the difference between the 2010 and 2015 indices) between 2010 and 2015 in 12 districts with and 30 districts without the RBF program for six maternal health outcomes (receipt of four or more prenatal care visits, initiation of prenatal care in the first trimester, delivery in a health facility, professional delivery assistance, delivery by caesarean section (C-section) and use of modern contraceptive methods (or family planning)). A negative value of the difference in differences indicates greater improvement in wealth-related inequalities in maternal health outcomes in RBF districts compared with non-RBF districts and vice versa. In other words, this observation shows that wealth-related inequalities in maternal health declined faster in RBF districts than they did in non-RBF districts. We observed improvements in equity for prenatal care (four or more visits) and use of modern contraceptive methods in RBF districts compared to non-RBF districts. Specifically, the results show equity improvements in the receipt of four or more prenatal care visits by an estimated 0.067 points and statistically significant at the 1 % level. This result can also be interpreted as a decline in inequality by 0.067. The results also show that, the gap between the rich and poor in terms of use of modern contraceptive methods declined faster in RBF districts than it did in non-RBF districts as shown by the difference-in-difference estimate of -0.023 and statistically significant at the 1% level.

Table 2: Difference-in-difference estimates of the distributional impact of the RBF program on wealth-related inequalities in selected maternal health outcomes in Zimbabwe

Specification	Prenatal care visits (4+)	First trimester prenatal care	Facility delivery	Professional delivery	C-section delivery	Family planning
Difference-in-differences estimate	**-0.067*** **	0.037***	0.055***	0.094***	0.029***	**-0.023*** **
	(0.006)	(0.008)	(0.009)	(0.010)	(0.004)	(0.006)
Observations	19,155	19,121	19,155	19155	14,010	19,155
Pre-policy inequality, non-RBF districts	0.0666	0.0633	0.247	0.250	0.0720	0.122
Pre-policy inequality, RBF districts	0.161	0.0366	0.283	0.233	0.0442	0.0869
Pre-policy difference in inequality	0.0949	-0.0267	0.0359	-0.0166	-0.0278	-0.0352
Post-policy inequality, non-RBF districts	0.101	0.0458	0.153	0.165	0.0643	0.132
Post-policy inequality, RBF districts	0.128	0.0562	0.244	0.242	0.0660	0.0744
Post-policy difference in inequality	0.0275	0.0103	0.0904	0.0775	0.00163	-0.0579

Notes: Table shows estimates from a DD model combined with kernel propensity-score matching. The signs ***, **, and ** indicate statistical significance at the 1, 5 and 10 percent levels, respectively. Concentration indices based on household wealth were used to measure inequities in maternal health outcomes (shown in each column). In parentheses, are bootstrapped standard errors calculated with 1000 replications to enhance the precision of the estimates. The bottom section of the Table shows average inequities before (2010) and after (2015) the intervention for RBF (n=12) and non-RBF districts (n=30). All the DD models included the following as additional control variables: years of completed schooling, age of the woman at childbirth, household size, number of health facilities within a 20 kilometre radius of the cluster centroid, and dummy variables for household wealth quintiles, female head of household, urban residence, and province of residence.

The results in Table 2 also indicate that the difference in differences estimates for first trimester prenatal care, facility delivery, professional delivery assistance, and C-section delivery were all positive indicative of improvements in the distribution of inequality in favour of non-RBF districts compared to RBF districts. These results show that inequality improved more markedly in non-RBF districts as opposed to RBF districts. For instance, inequality increased by 0.037 for first trimester prenatal care, 0.055 for facility delivery, 0.094 for professional delivery assistance and 0.029 for C-section delivery.

Table 3 summarises the results of the impact of RBF program on wealth-related inequality of quality of prenatal care including its content or components. The results show a greater improvement in equity in RBF districts than in non-RBF districts in terms of overall quality of prenatal care and statistically significant at the 1% level. Negative values of the difference in differences – suggestive of greater improvement in equity in RBF compared to non-RBF districts were observed for blood pressure checks, urine sample, and iron tablets and tetanus toxoid vaccinations. Specifically, the distribution in equity in these outcomes improved by 0.017, 0.001, 0.081 and 0.07 and statistically significant at the 10 and 1% levels, respectively with the exception of urine sample checks. The difference in difference estimate for blood sample checks was positive (0.132) indicating greater improvements in equity in non-RBF districts as compared to non-RBF districts and statistically significant at the 1% level.

Table 3: Difference-in-difference estimates of the distributional impact of the RBF program on wealth-related inequalities in quality of prenatal care in Zimbabwe

Specification	Prenatal quality index	Blood pressure	Urine sample	Blood sample	Iron tablets	Tetanus vaccination
Difference-in-differences estimate	-0.050***	-0.017*	-0.001	0.132***	-0.081***	-0.070***
	(0.008)	(0.007)	(0.009)	(0.007)	(0.007)	(0.007)
Observations	19,155	19,155	19,155	19,155	19,155	19,155
Pre-policy inequality, non-RBF districts	0.121	0.0997	0.102	0.135	0.0610	0.00456
Pre-policy inequality, RBF districts	0.246	0.192	0.178	0.0907	0.162	0.117
Pre-policy difference in inequality	0.125	0.0927	0.0768	-0.0439	0.101	0.112
Post-policy inequality, non-RBF districts	0.0917	0.0722	0.163	0.0659	0.0223	0.0429
Post-policy inequality, RBF districts	0.167	0.148	0.239	0.154	0.0420	0.0855
Post-policy difference in inequality	0.0754	0.0757	0.0756	0.0879	0.0197	0.0427

Notes: Table shows estimates from a DD model combined with kernel propensity-score matching. The signs ***, **, and ** indicate statistical significance at the 1, 5 and 10 percent levels, respectively. Concentration indices based on household wealth were used to measure inequities in maternal health outcomes (shown in each column). In parentheses, are bootstrapped standard errors calculated with 1000 replications to enhance the precision of the estimates. The bottom section of the Table shows average inequities before (2010) and after (2015) the intervention for RBF and non-RBF districts. All the DD models included the following as additional control variables: years of completed schooling, age of the woman at childbirth, household size, number of health facilities within a 20 kilometre radius of the cluster centroid, and dummy variables for household wealth quintiles, female head of household, urban residence, and province of residence.

6.5 Distributional impact of RBF on wealth-related inequalities in selected child health outcomes

Table 4 shows a summary of the results examining the equity impact of RBF program on selected child health outcomes. The results show that full immunization coverage for children has become less concentrated among the non-poor group in RBF districts as compared to non-RBF districts. Thus, we observed an improvement in equity in immunization coverage by about 0.143 and statistically significant at the 1% level. This result is made clear as we observe that for the RBF districts inequalities in immunisation coverage stood at 0.0758 (pro-rich) in 2010 and declined to 0.00627 in 2015. Despite the fact that the distribution of immunization coverage remains pro-rich in RBF districts, the gap between the rich and poor has become much narrower. The results also show that the change in the concentration indices for completion of child postnatal care within the first two months after birth before and after RBF implementation was 0.099 and statistically significant at the 1% level. This result shows that inequalities in postnatal checks for children within the first two months after birth remain to the advantage of the relatively wealthy families in RBF districts compared with the non-RBF districts.

Table 4: Difference-in-difference estimates of the distributional impact of the RBF program on wealth-related inequalities in selected child health outcomes in Zimbabwe

Specification	Postnatal check within two months	Full immunizations	Low birthweight	Neonatal mortality	Stunting
Difference-in-difference estimate	0.099***	-0.142***	-0.030***	-0.007***	-0.080***
	(0.005)	(0.018)	(0.004)	(0.001)	(0.006)
Observations	19,155	17,207	19,021	19,021	19,099
Pre-policy inequality, non-RBF districts	0.150	0.0415	-0.0166	-0.0129	-0.0897
Pre-policy inequality, RBF districts	0.121	0.0761	-0.0291	-0.0112	-0.00578
Pre-policy difference in inequality	-0.0294	0.0346	-0.0125	0.00170	0.0839
Post-policy inequality, non-RBF districts	0.0422	0.114	-0.00798	-0.00271	-0.0982
Post-policy inequality, RBF districts	0.112	0.00627	-0.0503	-0.00816	-0.0948
Post-policy difference in inequality	0.0695	-0.107	-0.0424	-0.00545	0.00346

Notes: Table shows estimates from a DD model combined with kernel propensity-score matching. The signs ***, **, and ** indicate statistical significance at the 1, 5 and 10 percent levels, respectively. Concentration indices based on household wealth were used to measure inequities in selected child health outcomes (shown in each column). In parentheses, are bootstrapped standard errors calculated with 1000 replications to enhance the precision of the estimates. The bottom section of the Table shows average inequities before (2010) and after (2015) the intervention for RBF and non-RBF districts. All the DD models included the following as additional control variables: child's birth order, child's gender, mother's years of completed schooling, age of the mother at childbirth, household size, number of health facilities within a 20 kilometre radius of the cluster centroid, and dummy variables for household wealth quintiles, female head of household, urban residence, and province of residence.

The results in Table 4 also show the changes in the concentration indices for ill-health outcomes for children as measured by low birth weight, neonatal mortality and stunting. The results indicate a deterioration in inequality in these outcomes. In other words, the ill-health outcomes remain highly concentrated among the relatively poor families in RBF districts compared to non-RBF districts and all statistically significant at the 1% level. For low birth weight, we observed a change in inequality from -0.0292 in 2010 to -0.0503 in RBF districts as compared with a change from -0.0166 in 2010 to -0.00794 in non-RBF districts. Wealth-driven differences in neonatal mortality changed from -0.0113 in 2010 to -0.00816 in 2015 in RBF districts as compared with a change from -0.0129 in 2010 to -0.00277 in 2015 in non-RBF districts. For stunting, we observed a change in inequality from -0.00572 in 2010 to -0.0948 in 2015 in RBF districts as compared to the change from -0.0892 in 2010 to -0.0984 in 2015 in non-RBF districts.

Table 5 presents the results examining the impact of RBF program on inequality in other child health and or health service utilisation outcomes. The results show that the probability that a child has had diarrhoea in the two weeks before each survey is highly concentrated among children from poor families in RBF districts as compared to non-RBF districts and statistically significant at the 1% level. The difference in difference estimate for diarrhoea was -0.017. We observed that wealth-related inequality in the prevalence of diarrhoea changed from 0.00661 in 2010 to -0.00479 in 2015 for RBF districts compared with a change from -0.0109 in 2010 to -0.00578 in 2015 for non-RBF districts. This result shows that the distribution of wealth-related inequalities in diarrhoea has become more pro-poor in RBF districts than it is in non-RBF districts. The change in the concentration indices for the probability that children receive treatment for diarrhoea has become less concentrated among the poor in RBF districts compared to non-RBF districts. Table 5 also shows the changes in the concentration indices for fever the probability of getting a fever in the two weeks before each survey and the prospect of receiving treatment for the fever. The changes in the concentration indices for these outcomes show improvements in inequality (i.e. they have become more concentrated among the poor in RBF districts as compared to non-RBF districts. We observed that the probability of having a fever has become less concentrated among children from poor families while that of receiving treatment for the fever has become highly concentrated among children from poor families in RBF districts compared to non-RBF districts respectively and all statistically significant at the 1% level.

Table 5: Difference-in-difference estimates of the distributional impact of the RBF program on wealth-related inequalities in selected child health outcomes in Zimbabwe

Specification	Diarrhoea in last two weeks	Diarrhoea treatment	Fever in last two weeks	Fever treatment
Difference-in-difference estimate	-0.017***	0.272***	0.058***	-0.259***
	(0.001)	(0.014)	(0.002)	(0.009)
Observations	18,875	18,645	19,193	18,851
Pre-policy inequality, non-RBF districts	-0.0109	0.0398	0.00432	0.0437
Pre-policy inequality, RBF districts	0.00661	-0.0880	-0.0355	0.208
Pre-policy difference in inequality	0.0175	-0.128	-0.0398	0.164
Post-policy inequality, non-RBF districts	-0.00578	-0.0312	0.00141	0.0859
Post-policy inequality, RBF districts	-0.00479	0.113	0.0195	-0.00925
Post-policy difference in inequality	0.000991	0.145	0.0181	-0.0951

Notes: Table shows estimates from a DD model combined with kernel propensity-score matching. The signs ***, **, and ** indicate statistical significance at the 1, 5 and 10 percent levels, respectively. Concentration indices based on household wealth were used to measure inequities in selected child health outcomes (shown in each column). In parentheses, are bootstrapped standard errors calculated with 1000 replications to enhance the precision of the estimates. The bottom section of the Table shows average inequities before (2010) and after (2015) the intervention for RBF and non-RBF districts. All the DD models included the following as additional control variables: child's birth order, child's gender, mother's years of completed schooling, age of the woman at childbirth, household size, number of health facilities within a 20 kilometre radius of the cluster centroid, and dummy variables for household wealth quintiles, female head of household, urban residence, and province of residence.

6.6 Test for parallel trends in wealth-related inequality in maternal and child health outcomes

The results for the tests comparing the pre-policy trends for RBF and non-RBF districts are presented as an appendix. Table A1 shows the tests for parallel trends for the outcomes representing wealth-related inequality in maternal health. The results in Table A1 indicate that there is no evidence to suggest that the parallel trends assumption is violated for maternal health outcomes relating to the receipt of four or more prenatal care visits ($p < 0.41$), first trimester prenatal care (0.66), professional delivery assistance (0.16), delivery by C-section ($p < 0.22$) and use of modern contraceptive methods ($p < 0.60$). However, the results for delivery in a health facility appear to suggest that the parallel trends assumption is violated ($p < 0.03$). Table A2 presents the results for the tests for parallel trends for outcomes related to the quality of received prenatal care. There is no evidence to suggest that the parallel trends assumption is violated for outcomes related to the overall quality or content of received prenatal care ($p < 0.14$), blood pressure check ($p < 0.30$), urine sample test ($p < 0.96$), and the receipt of iron tablets ($p < 0.42$).

However, the results seem to suggest that outcomes related to blood sample check, and tetanus vaccinations seem to suggest that that parallel trends assumption is violated for these outcomes. Overall, the results for the test for parallel trends suggest that the DD methodology appears appropriate for estimating the impact of the RBF program on wealth-related inequality of several maternal health care outcomes.

Table A3 presents the results for the tests comparing the pre-policy trends for the outcomes relating to inequalities in selected child health outcomes. The results indicate that there is no evidence to suggest that the parallel trends assumption is violated for child health outcomes pertaining to postnatal check-up ($p < 0.63$), full immunizations ($p < 0.55$), low birth weight ($p < 0.37$) and stunting (0.73). The parallel trends assumption appears to be violated for outcomes relating to the probability of neonatal mortality ($p < 0.02$). Table A4 presents the results for the tests of pre-policy trends for the outcomes relating to inequalities in other child health outcomes. In this instance, the results show that the parallel trends assumption is not violated for outcomes relating to diarrhoea in the last two weeks ($p < 0.55$). The results pertaining to outcomes relating to diarrhoea treatment ($p < 0.03$), fever in last two weeks ($p < 0.004$) and fever treatment ($p < 0.006$) show that the parallel trends assumption is violated for these outcomes.

6.7 Robustness checks – alternative measures of health inequality

As described earlier, we consider two alternative measures of health inequality, namely, generalized Gini index and SII. Both are absolute measures of health inequality. In this instance, we re-estimated our main empirical specification to test the sensitivity of our main estimates to alternative measures of health inequality. The results for these analyses are presented as supplementary material in the appendix (see Tables A6-A13). Table A6 shows the results for selected maternal health outcomes when we measure inequality using the SII. The results appear to be weakly robust given that the estimates for inequalities in first trimester care show an opposite sign when compared to the estimates in Table 2 when we use a relative measure of inequalities. Table A10 shows equivalent sets of results but this time when we measure inequalities using the generalized concentration index or generalized Gini. In this instance, the coefficients for prenatal care visits (4+ visits) are comparable to those in Table 2 i.e. (-0.048 vs -0.067. The coefficients on facility delivery and professional delivery indicate an improvement in health inequality (in absolute terms) and to the advantage of RBF districts. Overall, we can conclude that the results are fairly robust to the consideration of an alternative measure of inequalities. However, we wish to point out that the two inequality indices (CI vs SII or generalized CI) are not necessarily comparable since they measure a different dimension of inequality. What we compare in this case is the fact that RBF has had some impact on the distribution of inequalities whether in relative or absolute terms.

Table A7 and Table A11 report the results for prenatal care quality and the components of prenatal care. The estimates in Table A7 are generated when we use the SII. The results here show that blood pressure checks, urine sample checks, receipt of iron tablets all indicate significant improvements in RBF districts when compared to non RBF districts. In Table A11, all coefficients indicate significant improvements in equality of prenatal care content within RBF districts. Tables A8 and A12 report the estimates for the outcomes for children. The results here also indicate that our main estimates are mostly robust to the consideration of alternative measures of inequality. In this case, our conclusion based on Table 2 estimates are not necessarily altered with the exception of few outcomes which appear to show changing signs when we use SII and generalized Gini. The same can be said for results reported in Tables A9 and Table A13 for the second set of child outcomes. We noted few changes in the reported signs and magnitude of coefficients but overall the results are weakly robust.

7. Discussion

The RBF program was intended to enhance health system functionality and priority maternal and child health outcomes (World Bank, 2016). Zimbabwe is amongst several countries in Africa to have introduced the program in a gradual fashion in rural and low-income urban areas to improve health service delivery. Given that the program aimed at increasing both the quantity and quality of health services through its "results-based contracting" component, it makes sense to explore the extent to which the program has impacted the distribution of inequalities in selected maternal and child health outcomes. Implementation of the RBF program is more likely to improve access to health services by the poor or disadvantaged groups of the population since one of its provisions entails the abolition of user fees. Previous studies for Zimbabwe have explored the extent to which the program has impacted access to maternal and child health outcomes directly (see for example) with nothing yet known regarding the impact of the program on wealth-related inequality of maternal and child health outcomes.

To the best of our knowledge, this is the first study providing empirical evidence regarding the impact of the RBF program on inequality of maternal and child health outcomes and access across socioeconomic gradients in Zimbabwe using a DD approach complemented by kernel propensity score matching technique. Our approach measures socioeconomic status-driven inequalities in maternal and child health outcomes using the corrected concentration index. The empirical analysis compares the changes in concentration indices between 2010 and 2015 in 10 districts with and 30 districts without the RBF program for 12 indicators of access to maternal health care (i.e. receipt of four or more prenatal care visits), prenatal care in the first trimester, health facility delivery, delivery by C-section, professional delivery assistance, use of modern contraceptive methods, prenatal care quality index, receipt of the following services during prenatal care (blood pressure check, blood sample test, urine sample check, iron tablets, and receipt of tetanus toxoid vaccinations)) and nine indicators of child health outcomes (such as child postnatal care, full immunizations, low birthweight, neonatal mortality, stunting, diarrhoea in the last two weeks, diarrhoea treatment, fever in the last two weeks, and fever treatment). The empirical analysis shows how equity assessments can be integrated into impact evaluation frameworks that combine quasi experimental methods such as the difference-in-differences and kernel matching. We are not the first to conduct such kind of analyses (see e.g. (Masanja, Schellenberg, De Savigny, Mshinda, & Victora, 2005)). Masanja and colleagues evaluated the impact of the Integrated Management of Childhood Illness (IMCI) strategy on the equality of health outcomes and access across socioeconomic gradients in rural Tanzania through a comparison of inequalities before (1999) and after (2002) the implementation of the programme in two districts with and without the intervention (Masanja et al., 2005).

Recent evaluation work by the World Bank has shown that the RBF program in Zimbabwe was associated with improvements in delivery outcomes (delivery by skilled health professional, delivery in a health facility, and C-section delivery). This evaluation work has also shown that the RBF program in Zimbabwe was associated with increased chances that women received antenatal care from skilled or qualified health providers. The program was also associated with reductions in child stunting and underweight, and minimal to no improvements in family planning and child health services (World Bank, 2016). Their preliminary evaluation of the equity impact of RBF revealed that the program has a pro-poor or pro-marginalised group effects as reflected by the two dimensions in terms of education and socioeconomic status (World Bank, 2016). The latter result is somewhat consistent with some of our findings for certain outcomes and not all.

The results indicate that the RBF program in Zimbabwe was associated with greater and significant improvements in equity related to the frequency of prenatal care (receipt of four or more visits), family planning (use of modern contraceptive methods), and the overall quality of prenatal care (in terms of the content of care received). We also found that the RBF program was associated with improvements in equity in some components of prenatal care including blood pressure checks, receipt of iron tablets and tetanus toxoid vaccinations. These results underscore the importance of the RBF program in ameliorating unjustifiable inequalities in access to maternal health care created by differences in socioeconomic status. These results suggest that the RBF program in Zimbabwe has a pro-poor impact. This finding is somewhat consistent with the findings by the World Bank (World Bank, 2016). Our results also show that non-RBF districts experienced faster declines in inequality of delivery care outcomes (facility delivery, professional delivery, and C-section delivery) and first trimester prenatal care when compared with RBF districts. Previous research in Zimbabwe has shown that wealth-related inequalities in delivery care have been increasing between 1994 and 2011 (C. Makate, Makate, & Mango, 2019).

We also examined the distributional effect of the RBF program on selected child health outcomes in Zimbabwe. We found that non-RBF districts experienced faster declines in inequality of postnatal care for children when compared to RBF districts. The results also show that the RBF program was associated with greater improvements in equity of child full immunizations. This finding is consistent with the findings from a study evaluating the distributional impact of an RBF program on child immunizations in Canada (Katz et al., 2015). In this study, while the RBF program did not eradicate inequalities in child immunizations, the program helped to narrow the gap between the rich and the poor. Our results also show that the RBF program was associated with significant and faster improvements in equity of fever treatment among children under five years of age. However, the RBF program did not appear to ameliorate wealth-related inequality in terms of child low birth weight, neonatal mortality, stunting, diarrhoea, diarrhoea treatment and fever. These results are largely consistent with the findings by the World Bank in the context of Zimbabwe (World Bank, 2016). The general conclusion by the World Bank was that the RBF program in Zimbabwe did not appear to have significant improvements in child health outcomes among the relatively poor (World Bank, 2016). Overall, our results show that the impact of the RBF program on equity of maternal and child health outcomes in Zimbabwe was not uniform.

Study strengths and limitations

Our study is not without its limitations. First, we mostly rely on cross sectional data, which has its own limitations. Second, the GPS locational data we use is subject to a random error as described earlier in the text. This displacement could potentially impact our results. However, given the random nature of this displacement, we have no reason to believe that the displacement effect was specifically designed such that it incorporated the potential distributional impact of the RBF program. Third, our analysis only considers districts in which the overall number of observations in each survey was 20 or more in order to minimise problems associated with sparse data (i.e. minimising sparse data bias). Thus, we exclude other districts where the data on our outcomes of interest was not available. This, is likely to create a potential bias in our estimates. We cannot do anything about the latter limitation as it is the nature of the data we use. Lastly, the parallel trends assumption does not hold for just a few of our outcome variables hence, we interpret the results for these outcomes with caution. Nevertheless, we make vital contributions to the literature regarding the distributional impact of RBF programs on wealth-based inequalities in access to maternal and child health outcomes in low-income countries such as Zimbabwe.

8. Conclusions and policy insights

From a policy standpoint, it is imperative to know whether implemented policies or interventions designed to improve quantity and quality of health services and reduce socioeconomic status-connected inequalities have the direct and intended consequences of meeting their primary objectives over time. Our analysis of nationally representative survey data from Zimbabwe shows that the RBF program was associated with faster improvements in equity of selected maternal and child health outcomes in Zimbabwe. We also established that the distributional impact of this program was not uniform across maternal and child health outcomes. In other words, the program appeared to favour equity of some health outcomes over others. Thus, future roll-out of this program could deliberately be tailored to be specific to particular contexts, bearing in mind that the program may not have similar distributional effects on certain outcomes. Such initiatives would carefully examine the socio-economic context among other things, in the design and execution of the program in order to maximise the impact of such initiatives. These results have important implications for public health policies targeted at improving access to maternal health care services to pregnant women in developing countries like Zimbabwe. These results are also important inputs to future research interested in evaluating whether RBF strategies are good value for money or not. Our analysis clearly reveals that RBF programs do not necessarily eliminate wealth-related inequality in maternal and child health outcomes in Zimbabwe but are certainly a useful complement to equity-enhancing initiatives/policies in the country.

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List of appendices

Table A1: Test for parallel trends in wealth-related inequality in maternal health care outcomes, 1999-2010

Specification	Prenatal care visits (4+)		Prenatal care (1st trimester)		Facility delivery		Professional delivery		Delivery by C-section		Family planning	
RBF district × survey year												
RBF × 1999	0.03	(0.07)	-0.06	(0.09)	-0.05	(0.09)	-0.05	(0.09)	0.01	(0.04)	-0.04	(0.10)
RBF × 2005	0.16	(0.10)	0.09	(0.10)	0.19	(0.10)	0.14	(0.11)	0.06	(0.04)	-0.08	(0.07)
RBF × 2010	0.04	(0.11)	0.02	(0.11)	-0.05	(0.14)	-0.10	(0.12)	-0.01	(0.05)	0.04	(0.09)
Observations	47383		47318		47370		47383		43254		47383	
p-value for F-test	0.41		0.66		0.03		0.16		0.22		0.60	

Notes: ***Significant at 1% level; **significant at 5% level; *significant at 10% level. Estimates are from linear probability models with errors (in parentheses) clustered at the district level. All models include controls for: RBF district indicator, dummy indicators for survey years 1999, 2005 and 2010, woman's years of schooling, age at childbirth, household size, female head of household, region fixed effects and region-year specific fixed effects. Zimbabwe DHS data for survey years 1999-2010 are used to generate the reported estimates.

Table A2: Test for parallel trends in wealth-related inequality in prenatal care quality outcomes, 1999-2010

Specification	Prenatal quality index		Blood pressure		Urine sample		Blood sample		Iron tablets		Tetanus vaccination	
RBF district × survey year												
RBF × 1999	-0.02	(0.10)	0.01	(0.08)	-0.02	(0.12)	-0.10	(0.11)	0.07	(0.06)	-0.05	(0.08)
RBF × 2005	0.20	(0.13)	0.11	(0.08)	0.03	(0.14)	0.27*	(0.12)	-0.05	(0.14)	0.25**	(0.08)
RBF × 2010	0.02	(0.10)	0.05	(0.07)	-0.00	(0.10)	-0.11	(0.11)	0.06	(0.07)	-0.05	(0.08)
Observations	47383		47383		47348		47370		47383		47361	
p-value for F-test	0.14		0.30		0.96		0.001		0.42		0.001	

Notes: ***Significant at 1% level; **significant at 5% level; *significant at 10% level. Estimates are from linear probability models with errors (in parentheses) clustered at the district level. All models include controls for: RBF district indicator, dummy indicators for survey years 1999, 2005 and 2010, woman's years of schooling, age at childbirth, household size, female head of household, region fixed effects and region-year specific fixed effects. Zimbabwe DHS data for survey years 1999-2010 are used to generate the reported estimates.

Table A3: Test for parallel trends in wealth-related inequality in selected child health outcomes, 1999-2010

Specifications	Postnatal check within two months		Full immunizations		Low birthweight (<2500 grams)		Neonatal mortality		Stunting (HAZ<-2SD)	
RBF district × survey year										
RBF × 1999			0.17	(0.13)	-0.02	(0.04)	0.02*	(0.01)		
RBF × 2005	0.07	(0.17)	0.11	(0.11)	0.06	(0.06)	-0.01	(0.01)	0.02	(0.07)
RBF × 2010	-0.06	(0.08)	0.16	(0.17)	0.06	(0.05)	-0.01	(0.01)	0.05	(0.06)
Observations	37102		46578		46155		46838		37193	
p-value for F-test	0.63		0.55		0.37		0.02		0.73	

Notes: ***Significant at 1% level; **significant at 5% level; *significant at 10% level. Estimates are from linear probability models with errors (in parentheses) clustered at the district level. All models include controls for: RBF district indicator, dummy indicators for survey years 1999, 2005 and 2010, woman's years of schooling, age at childbirth, household size, female head of household, region fixed effects and region-year specific fixed effects. Zimbabwe DHS data for survey years 1999-2010 are used to generate the reported estimates.

Table A4: Test for parallel trends in wealth-related inequality in selected child health outcomes, 1999-2010

Specification	Diarrhoea in last two weeks		Diarrhoea treatment		Fever in last two weeks		Fever treatment	
RBF district × survey year								
RBF × 1999	0.001	(0.013)	-0.271*	(0.126)	-0.017	(0.018)	-0.115	(0.080)
RBF × 2005	0.01	(0.016)	0.053	(0.121)	-0.026	(0.044)	-0.095	(0.134)
RBF × 2010	0.01	(0.011)	-0.307*	(0.144)	-0.060**	(0.023)	0.203	(0.114)
Observations	46996		46499		47245		46701	
p-value for F-test	0.55		0.031		0.004		0.006	

Notes: ***Significant at 1% level; **significant at 5% level; *significant at 10% level. Estimates are from linear probability models with errors (in parentheses) clustered at the district level. All models include controls for: RBF district indicator, dummy indicators for survey years 1999, 2005 and 2010, woman's years of schooling, age at childbirth, household size, female head of household, region fixed effects and region-year specific fixed effects. Zimbabwe DHS data for survey years 1999-2010 are used to generate the reported estimates.

Table A5: List of all the districts used for the main analysis

District name	RBF district		non-RBF district	
	Yes/No	Count	Yes/No	Count
Binga	Yes	675	No	n/a
Centenary	Yes	428	No	n/a
Chiredzi	Yes	736	No	n/a
Gwanda	Yes	385	No	n/a
Gweru	Yes	641	No	n/a
Kariba	Yes	301	No	n/a
Marondera	Yes	371	No	n/a
Mutare	Yes	867	No	n/a
Mutoko	Yes	423	No	n/a
Mwenezi	Yes	486	No	n/a
Nkayi	Yes	255	No	n/a
Zvishavane	Yes	289	No	n/a
Bindura	No	n/a	Yes	804
Bulawayo	No	n/a	Yes	1,942
Bulilima (North)	No	n/a	Yes	361
Chimanimani	No	n/a	Yes	332
Chipinge	No	n/a	Yes	848
Chivi	No	n/a	Yes	514
Gokwe North	No	n/a	Yes	506
Gokwe South	No	n/a	Yes	931
Guruve	No	n/a	Yes	553
Harare	No	n/a	Yes	3,684
Hurungwe	No	n/a	Yes	1,109
Hwange	No	n/a	Yes	659
Insiza	No	n/a	Yes	415
Kwekwe	No	n/a	Yes	475
Makonde	No	n/a	Yes	701
Mangwe (South)	No	n/a	Yes	343
Masvingo	No	n/a	Yes	684
Matobo	No	n/a	Yes	381
Mberengwa	No	n/a	Yes	498
Mount Darwin	No	n/a	Yes	389
Mudzi	No	n/a	Yes	353
Murehwa	No	n/a	Yes	551
Mutasa	No	n/a	Yes	392
Nyanga	No	n/a	Yes	429
Rushinga	No	n/a	Yes	288
Shurugwi	No	n/a	Yes	190
UMP	No	n/a	Yes	367
Umzingwane	No	n/a	Yes	237
Zaka	No	n/a	Yes	424
Zvimba	No	n/a	Yes	627

Total observations	5857	19987

Notes: The districts listed in the table are with regards to the data from the 2010 and 2015 Zimbabwe demographic and health surveys that was used for the main analysis.

Table A6: Difference-in-difference estimates of the distributional impact of the RBF program on absolute inequality in selected maternal health outcomes in Zimbabwe – robustness checks

Specification	Prenatal care visits (4+)	First trimester prenatal care	Facility delivery	Professional delivery	C-section delivery	Family planning
Difference-in-differences estimate	-0.200***	-0.066***	0.153***	0.155***	0.088***	0.037***
	(0.008)	(0.009)	(0.014)	(0.012)	(0.009)	(0.007)
Observations	18,686	18,627	18,627	18,627	11,187	18,686
Pre-policy inequality, non-RBF districts	-0.0208	0.0989	0.413	0.416	0.200	0.191
Pre-policy inequality, RBF districts	0.253	0.222	0.425	0.352	-0.00813	0.201
Pre-policy difference in inequality	0.274	0.123	0.0122	-0.0643	-0.208	0.00914
Post-policy inequality, non-RBF districts	0.136	0.0238	0.204	0.257	0.213	0.140
Post-policy inequality, RBF districts	0.210	0.0810	0.369	0.348	0.0932	0.186
Post-policy difference in inequality	0.0743	0.0572	0.165	0.0907	-0.120	0.0461

Notes: Table shows estimates from a DD model combined with kernel propensity-score matching. The signs ***, **, and ** indicate statistical significance at the 1, 5 and 10 percent levels, respectively. The slope index of inequality (SII) was used to measure inequities in maternal health outcomes (shown in each column). In parentheses, are bootstrapped standard errors calculated with 1000 replications to enhance the precision of the estimates. The bottom section of the Table shows average inequities before (2010) and after (2015) the intervention for RBF (n=12) and non-RBF districts (n=30). All the DD models included the following as additional control variables: years of completed schooling, age of the woman at childbirth, household size, number of health facilities within a 20 kilometre radius of the cluster centroid, and dummy variables for household wealth quintiles, female head of household, urban residence, and province of residence.

Table A7: Difference-in-difference estimates of the distributional impact of the RBF program on absolute inequality in quality of prenatal care in Zimbabwe – robustness checks

Specification	Blood pressure	Urine sample	Blood sample	Iron tablets	Tetanus vaccination
Difference-in-differences estimate [a]	-0.058***	-0.153***	0.059***	-0.069***	0.158***
	(0.012)	(0.012)	(0.009)	(0.009)	(0.009)
Observations	17219	18686	17669	18600	18480
Pre-policy inequality, non-RBF districts	0.142	0.0981	0.197	0.0998	0.161
Pre-policy inequality, RBF districts	0.236	0.358	0.251	0.222	0.0763
Pre-policy difference in inequality	0.0935	0.259	0.0536	0.122	-0.0849
Post-policy inequality, non-RBF districts	0.116	0.168	0.0573	0.0158	0.0605
Post-policy inequality, RBF districts	0.152	0.274	0.170	0.0687	0.133
Post-policy difference in inequality	0.0359	0.106	0.113	0.0530	0.0730

Notes: Table shows estimates from a DD model combined with kernel propensity-score matching. The signs ***, **, and ** indicate statistical significance at the 1, 5 and 10 percent levels, respectively. The slope index of inequality (SII) was used to measure inequities in maternal health outcomes (shown in each column). In parentheses, are bootstrapped standard errors calculated with 1000 replications to enhance the precision of the estimates. The bottom section of the Table shows average inequities before (2010) and after (2015) the intervention for RBF and non-RBF districts. All the DD models included the following as additional control variables: years of completed schooling, age of the woman at childbirth, household size, number of health facilities within a 20 kilometre radius of the cluster centroid, and dummy variables for household wealth quintiles, female head of household, urban residence, and province of residence.

Table A8: Difference-in-difference estimates of the distributional impact of the RBF program on absolute inequality in selected child health outcomes in Zimbabwe – robustness checks

Specification	Postnatal check within two months	Full immunizations	Low birthweight	Neonatal mortality	Stunting
Difference-in-difference estimate	0.130***	-0.074***	-0.034***	-0.028***	-0.264***
	(0.010)	(0.018)	(0.006)	(0.002)	(0.008)
Observations	18,363	15,743	18,714	17,755	18,681
Pre-policy inequality, non-RBF districts	0.188	-0.0449	-0.00990	-0.0130	-0.187
Pre-policy inequality, RBF districts	0.0746	-0.116	0.00621	-0.00637	0.0104
Pre-policy difference in inequality	-0.113	-0.0711	0.0161	0.00662	0.198
Post-policy inequality, non-RBF districts	0.116	0.147	-0.0262	0.00608	-0.0795
Post-policy inequality, RBF districts	0.133	0.00194	-0.0436	-0.0153	-0.146
Post-policy difference in inequality	0.0166	-0.145	-0.0174	-0.0214	-0.0664

Notes: Table shows estimates from a DD model combined with kernel propensity-score matching. The signs ***, **, and ** indicate statistical significance at the 1, 5 and 10 percent levels, respectively. The slope index of inequality (SII) was used to measure inequities in maternal health outcomes (shown in each column). In parentheses, are bootstrapped standard errors calculated with 1000 replications to enhance the precision of the estimates. The bottom section of the Table shows average inequities before (2010) and after (2015) the intervention for RBF and non-RBF districts. All the DD models included the following as additional control variables: years of completed schooling, age of the woman at childbirth, household size, number of health facilities within a 20-kilometer radius of the cluster centroid, and dummy variables for household wealth quintiles, female head of household, urban residence, and province of residence.

Table A9: Difference-in-difference estimates of the distributional impact of the RBF program on absolute inequality in selected maternal health outcomes in Zimbabwe – robustness checks

Specification	Diarrhoea in last two weeks	Diarrhoea treatment	Fever in last two weeks	Fever treatment
Difference-in-difference estimate	0.008***	-0.053***	0.067***	-0.230***
	(0.002)	(0.014)	(0.003)	(0.010)
Observations	18,371	14,069	18,562	18,125
Pre-policy inequality, non-RBF districts	0.00133	0.154	0.0204	0.0502
Pre-policy inequality, RBF districts	-0.0133	0.142	-0.0271	0.155
Pre-policy difference in inequality	-0.0146	-0.0123	-0.0475	0.104
Post-policy inequality, non-RBF districts	-0.00839	0.0982	-0.0131	0.161
Post-policy inequality, RBF districts	-0.0151	0.0329	0.00630	0.0357
Post-policy difference in inequality	-0.00669	-0.0653	0.0194	-0.125

Notes: Table shows estimates from a DD model combined with kernel propensity-score matching. The signs ***, **, and ** indicate statistical significance at the 1, 5 and 10 percent levels, respectively. The slope index of inequality (SII) was used to measure inequities in selected child health outcomes (shown in each column). In parentheses, are bootstrapped standard errors calculated with 1000 replications to enhance the precision of the estimates. The bottom section of the Table shows average inequities before (2010) and after (2015) the intervention for RBF and non-RBF districts. All the DD models included the following as additional control variables: child's birth order, child's gender, mother's years of completed schooling, age of the woman at childbirth, household size, number of health facilities within a 20 kilometre radius of the cluster centroid, and dummy variables for household wealth quintiles, female head of household, urban residence, and province of residence.

Table A10: Difference-in-difference estimates of the distributional impact of the RBF program on absolute inequality in selected maternal health outcomes in Zimbabwe – robustness checks

Specification	Prenatal care visits (4+)	First trimester prenatal care	Facility delivery	Professional delivery	C-section delivery	Family planning
Difference-in-difference estimate	-0.048***	0.039***	-0.068***	-0.060***	0.007***	-0.023***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)
Observations	13,232	12,912	13,232	13,232	11,791	13,232
Pre-policy inequality, non-RBF districts	0.0482	0.0586	0.0524	0.0527	0.0260	0.0382
Pre-policy inequality, RBF districts	0.0880	0.0679	0.115	0.0988	0.0350	0.0620
Pre-policy difference in inequality	0.0398	0.00925	0.0623	0.0461	0.00902	0.0238
Post-policy inequality, non-RBF districts	0.0772	0.0642	0.0698	0.0724	0.0235	0.0580
Post-policy inequality, RBF districts	0.0692	0.112	0.0646	0.0586	0.0390	0.0585
Post-policy difference in inequality	-0.00800	0.0483	-0.00523	-0.0138	0.0156	0.000572

Notes: Table shows estimates from a DD model combined with kernel propensity-score matching. The signs ***, **, and ** indicate statistical significance at the 1, 5 and 10 percent levels, respectively. The generalized Gini index was used to measure absolute inequality in maternal health outcomes (shown in each column). In parentheses, are bootstrapped standard errors calculated with 1000 replications to enhance the precision of the estimates. The bottom section of the Table shows average inequities before (2010) and after (2015) the intervention for RBF and non-RBF districts. All the DD models included the following as additional control variables: years of completed schooling, age of the woman at childbirth, household size, number of health facilities within a 20 kilometre radius of the cluster centroid, and dummy variables for household wealth quintiles, female head of household, urban residence, and province of residence.

Table A11: Difference-in-difference estimates of the distributional impact of the RBF program on absolute inequality in selected maternal health outcomes in Zimbabwe – robustness checks

Specification	Prenatal quality index	Blood pressure	Urine sample	Blood sample	Iron tablets	Tetanus vaccination
Difference-in-difference estimate	-0.277***	-0.068***	-0.060***	-0.044***	-0.046***	-0.045***
	(0.009)	(0.001)	(0.002)	(0.002)	(0.002)	(0.001)
Observations	13,232	13,232	13,232	13,232	13,232	13,232
Pre-policy inequality, non-RBF districts	0.189	0.0260	0.0636	0.0384	0.0504	0.0319
Pre-policy inequality, RBF districts	0.392	0.0837	0.0997	0.0721	0.0983	0.0634
Pre-policy difference in inequality	0.203	0.0576	0.0361	0.0337	0.0479	0.0314
Post-policy inequality, non-RBF districts	0.257	0.0486	0.0922	0.0471	0.0591	0.0669
Post-policy inequality, RBF districts	0.182	0.0377	0.0686	0.0366	0.0606	0.0530
Post-policy difference in inequality	-0.0746	-0.0108	-0.0237	-0.0105	0.00154	-0.0138

Notes: Table shows estimates from a DD model combined with kernel propensity-score matching. The signs ***, **, and ** indicate statistical significance at the 1, 5 and 10 percent levels, respectively. The generalized Gini index was used to measure absolute inequality in maternal health outcomes (shown in each column). In parentheses, are bootstrapped standard errors calculated with 1000 replications to enhance the precision of the estimates. The bottom section of the Table shows average inequities before (2010) and after (2015) the intervention for RBF and non-RBF districts. All the DD models included the following as additional control variables: years of completed schooling, age of the woman at childbirth, household size, number of health facilities within a 20 kilometre radius of the cluster centroid, and dummy variables for household wealth quintiles, female head of household, urban residence, and province of residence.

Table A12: Difference-in-difference estimates of the distributional impact of the RBF program on absolute inequality in selected child health outcomes in Zimbabwe – robustness checks

Specification	Postnatal check within two months	Full immunizations	Low birthweight	Neonatal mortality	Stunting
Difference-in-differences estimate	-0.021***	-0.038***	0.017***	-0.000	0.005***
	(0.002)	(0.002)	(0.001)	(0.000)	(0.001)
Observations	12,743	12,122	12,436	12,210	12,811
Pre-policy inequality, non-RBF districts	0.0722	0.0995	0.0258	0.00629	0.0514
Pre-policy inequality, RBF districts	0.0803	0.136	0.0297	0.00918	0.0670
Pre-policy difference in inequality	0.00818	0.0368	0.00390	0.00289	0.0155
Post-policy inequality, non-RBF districts	0.0616	0.0944	0.0290	0.0116	0.0579
Post-policy inequality, RBF districts	0.0492	0.0935	0.0498	0.0140	0.0785
Post-policy difference in inequality	-0.0124	-0.000848	0.0208	0.00247	0.0206

Notes: Table shows estimates from a DD model combined with kernel propensity-score matching. The signs ***, **, and ** indicate statistical significance at the 1, 5 and 10 percent levels, respectively. The generalized Gini index was used to measure absolute inequality in maternal health outcomes (shown in each column). In parentheses, are bootstrapped standard errors calculated with 1000 replications to enhance the precision of the estimates. The bottom section of the Table shows average inequities before (2010) and after (2015) the intervention for RBF and non-RBF districts. All the DD models included the following as additional control variables: years of completed schooling, age of the woman at childbirth, household size, number of health facilities within a 20 kilometre radius of the cluster centroid, and dummy variables for household wealth quintiles, female head of household, urban residence, and province of residence.

Table A13: Difference-in-difference estimates of the distributional impact of the RBF program on absolute inequality in selected maternal health outcomes in Zimbabwe – robustness checks

Specification	Diarrhoea in last two weeks	Diarrhoea treatment	Fever in last two weeks	Fever treatment
Difference-in-difference estimate	-0.009***	-0.030***	-0.014***	0.036***
	(0.000)	(0.005)	(0.001)	(0.002)
Observations	12,188	12,188	13,030	12,460
Pre-policy inequality, non-RBF districts	0.00867	0.0529	0.00918	0.117
Pre-policy inequality, RBF districts	0.0159	0.0574	0.0208	0.121
Pre-policy difference in inequality	0.00719	0.00456	0.0116	0.00432
Post-policy inequality, non-RBF districts	0.0139	0.136	0.0248	0.0732
Post-policy inequality, RBF districts	0.0125	0.110	0.0226	0.113
Post-policy difference in inequality	-0.00144	-0.0250	-0.00216	0.0402

Notes: Table shows estimates from a DD model combined with kernel propensity-score matching. The signs ***, **, and ** indicate statistical significance at the 1, 5 and 10 percent levels, respectively. The generalized Gini index was used to measure absolute inequality in child health outcomes (shown in each column). In parentheses, are bootstrapped standard errors calculated with 1000 replications to enhance the precision of the estimates. The bottom section of the Table shows average inequities before (2010) and after (2015) the intervention for RBF and non-RBF districts. All the DD models included the following as additional control variables: years of completed schooling, age of the woman at childbirth, household size, number of health facilities within a 20 kilometre radius of the cluster centroid, and dummy variables for household wealth quintiles, female head of household, urban residence, and province of residence.

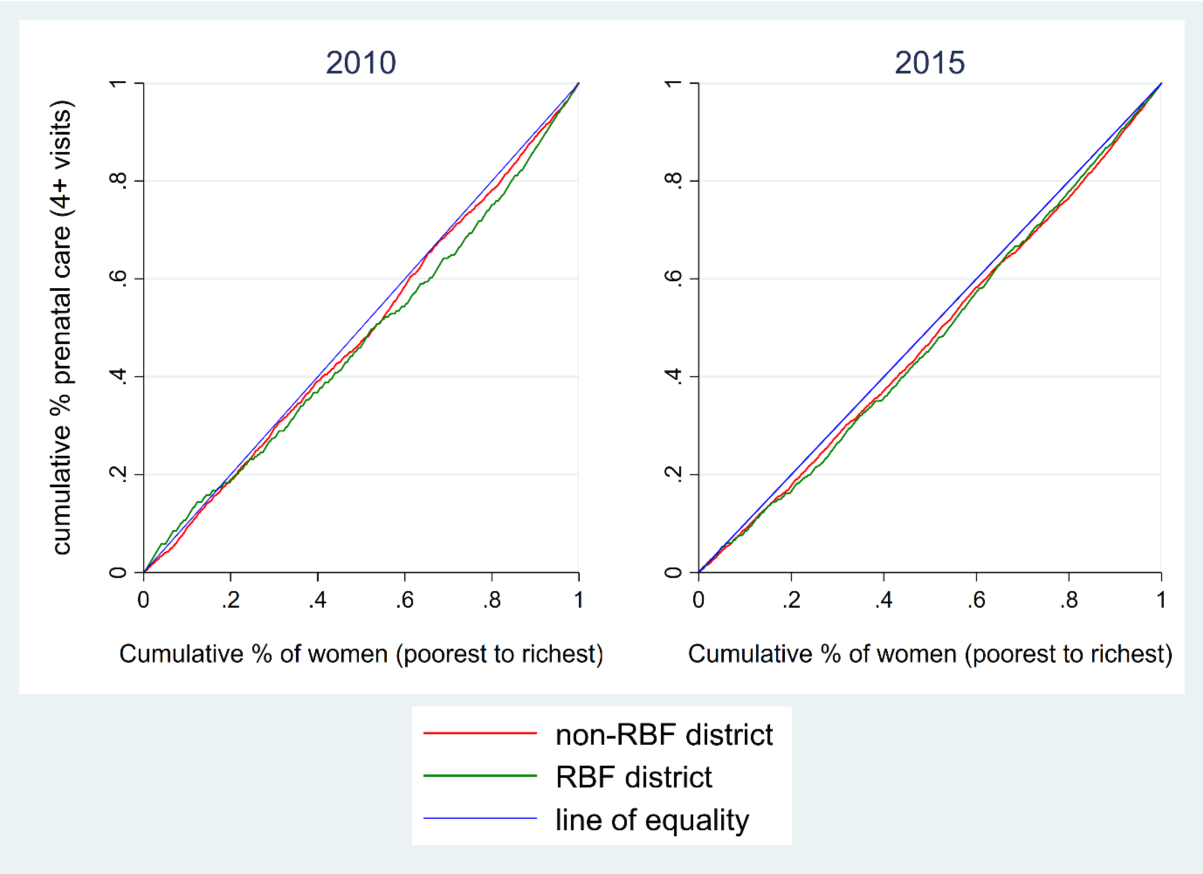

Figure A5. Distribution of concentration curves for receipt of four or more prenatal care visits in 2010 vs 2015 for RBF and non-RBF districts in Zimbabwe.

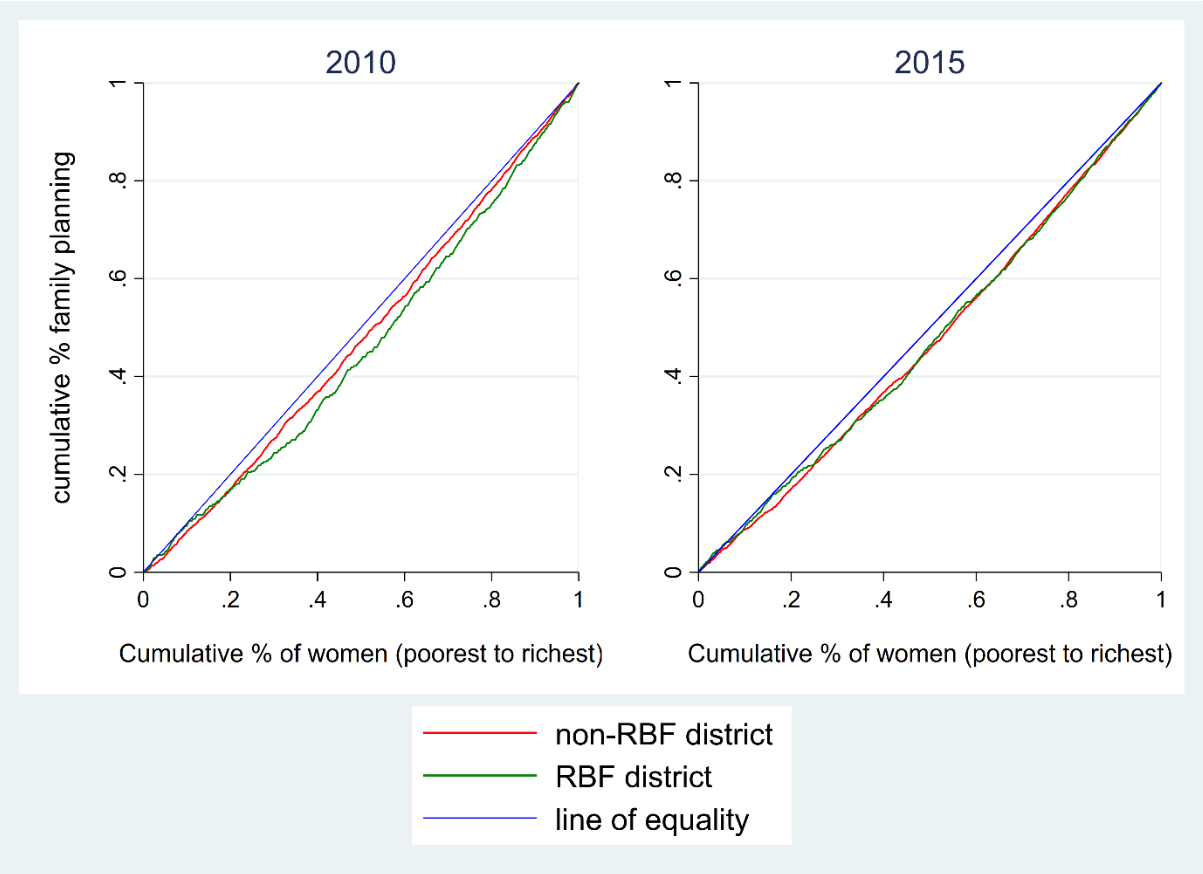

Figure A6. Distribution of concentration curves for use of modern contraceptive methods in 2010 vs 2015 for RBF and non-RBF districts in Zimbabwe.

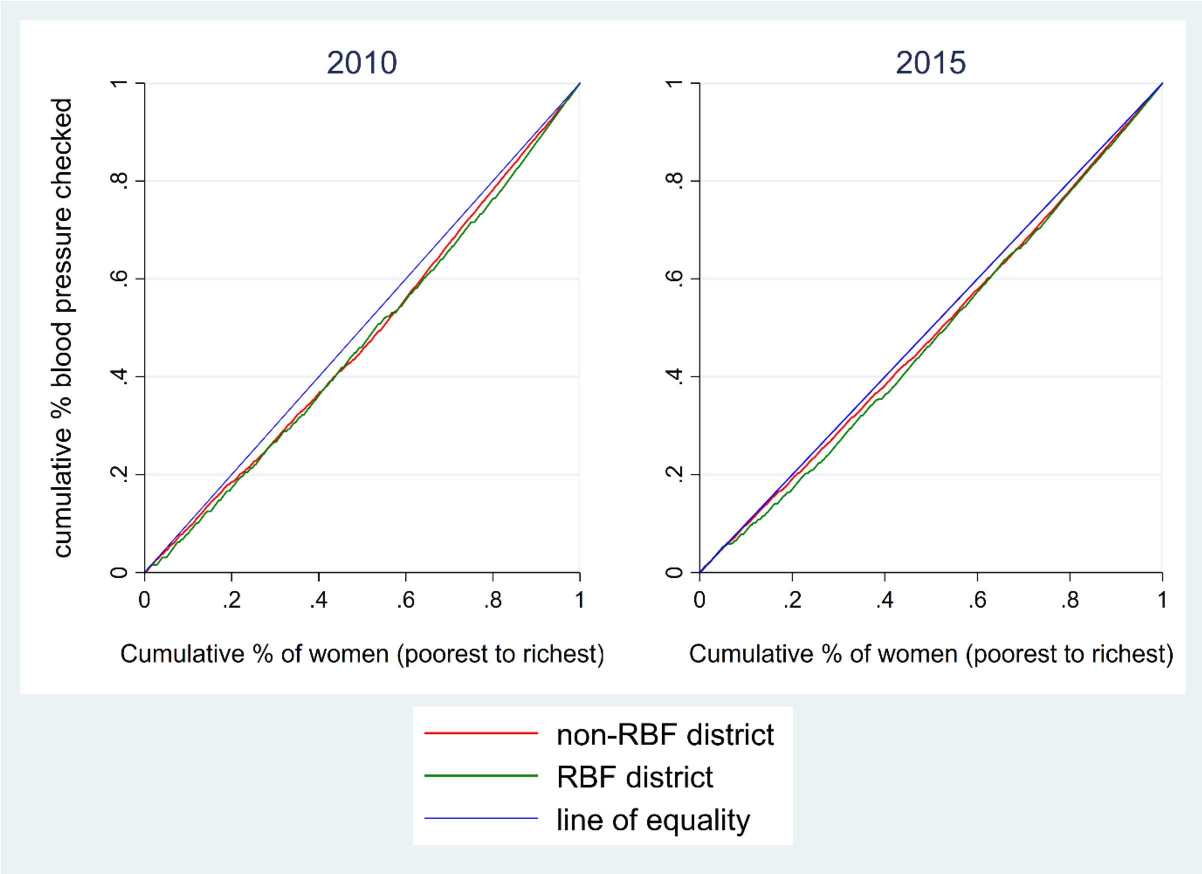

Figure A7. Distribution of concentration curves for receipt of blood pressure checks during prenatal care in 2010 vs 2015 for RBF and non-RBF districts in Zimbabwe.

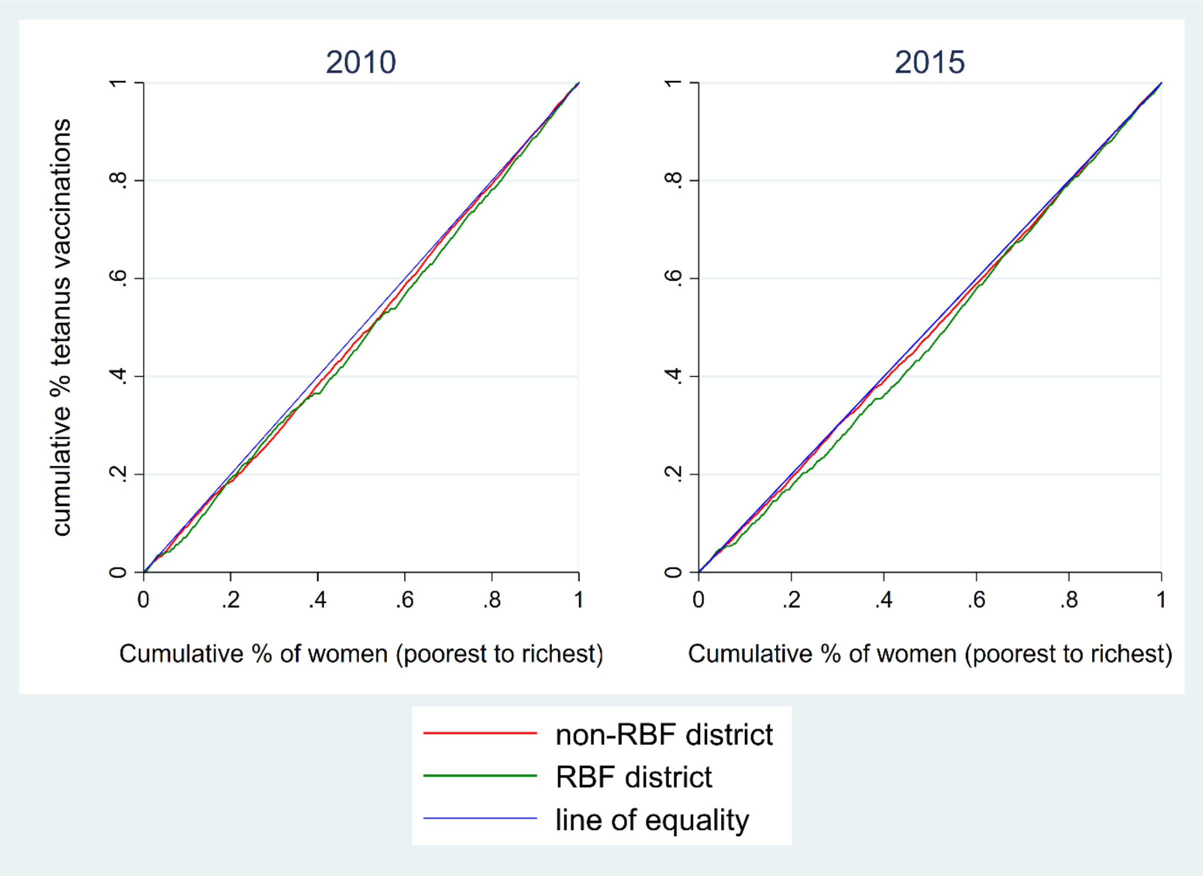

Figure A8. Distribution of concentration curves for receipt of tetanus toxoid vaccinations during prenatal care in 2010 vs 2015 for RBF and non-RBF districts in Zimbabwe.

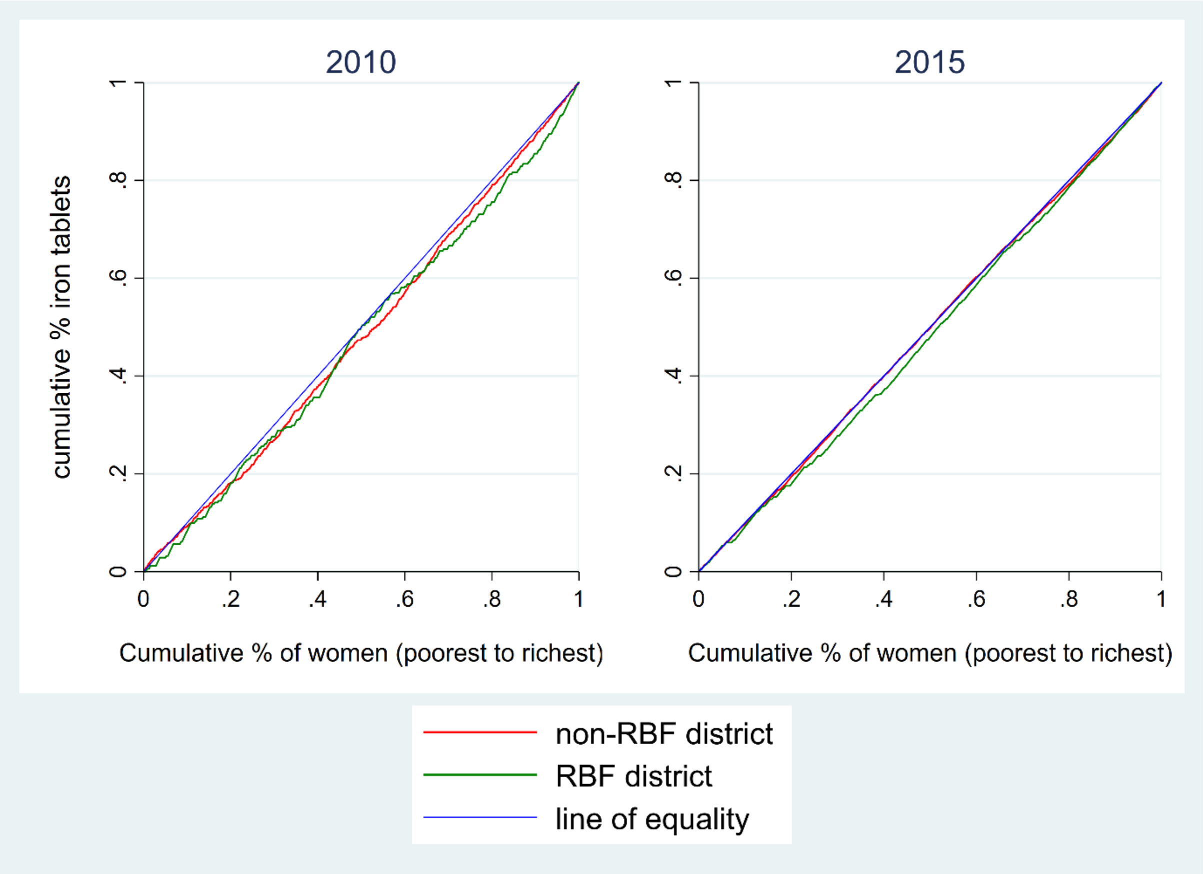

Figure A9. Distribution of concentration curves for receipt of iron tablets during prenatal care in 2010 vs 2015 for RBF and non-RBF districts in Zimbabwe.

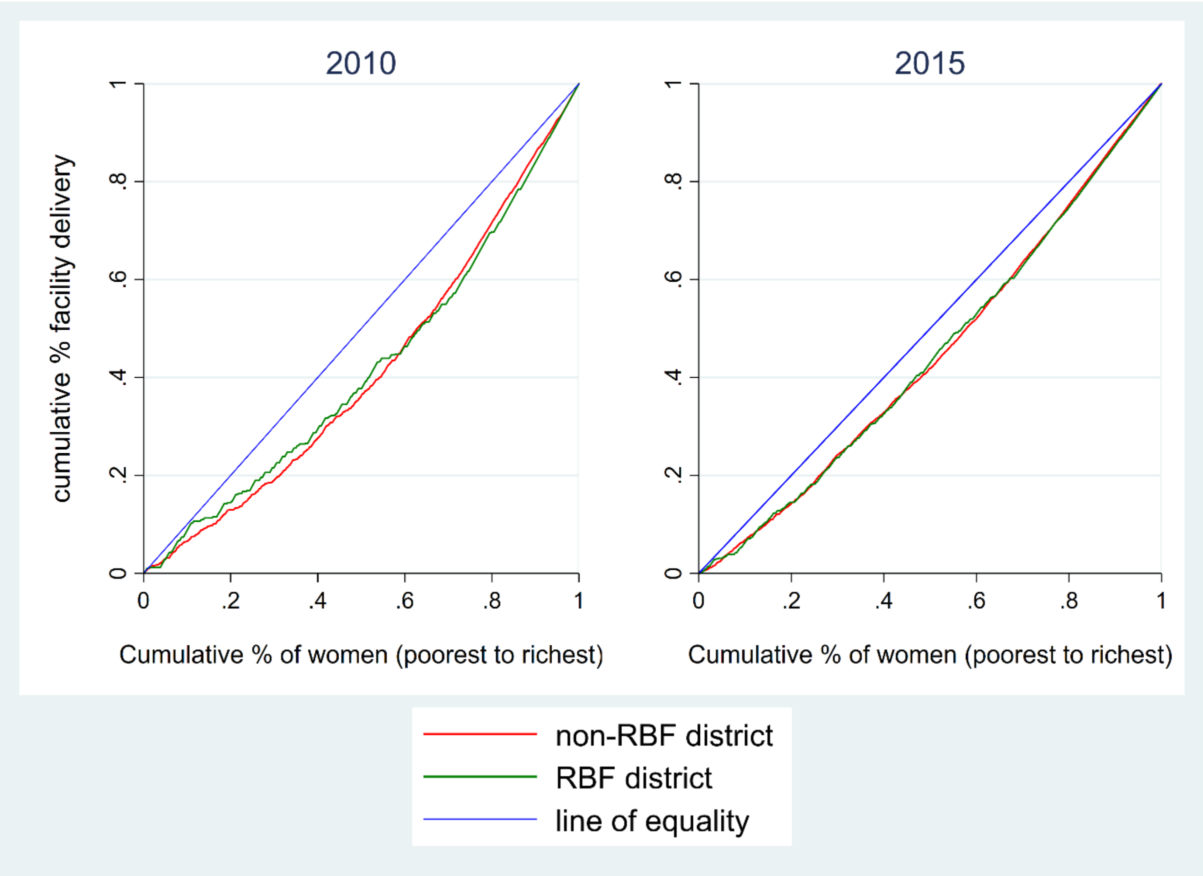

Figure A10. Distribution of concentration curves for facility delivery in 2010 vs 2015 for RBF and non-RBF districts in Zimbabwe.

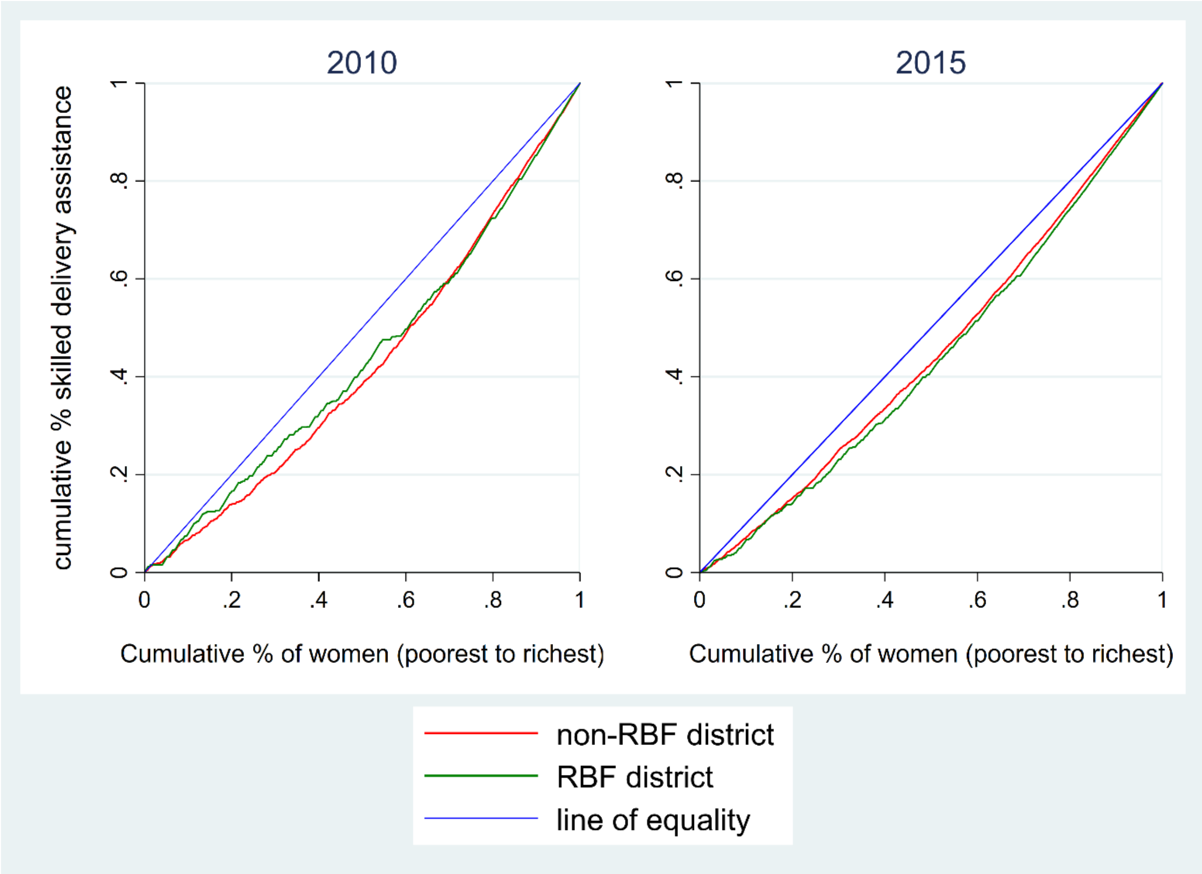

Figure A11. Distribution of concentration curves for skilled delivery assistance in 2010 vs 2015 for RBF and non-RBF districts in Zimbabwe.

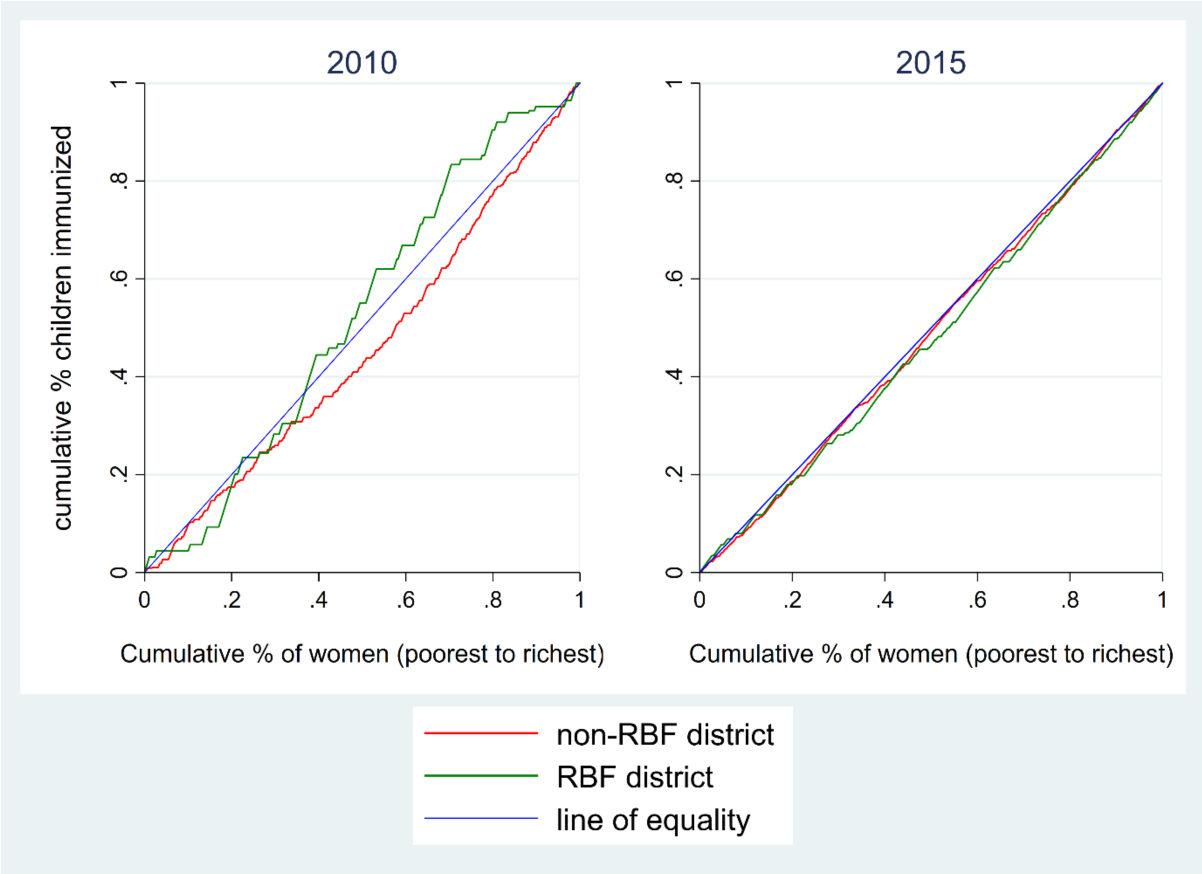

Figure A12. Distribution of concentration curves for child full immunizations in 2010 vs 2015 for RBF and non-RBF districts in Zimbabwe.

Figure A13. Distribution of concentration curves for fever treatment in the two weeks before the survey in 2010 vs 2015 for RBF and non-RBF districts in Zimbabwe.