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From subsidies to nutrition: Investigating effects among cohort children from the Subsidy Reinvestment programme in Nigeria

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ABSTRACT

This study investigates the effect of a nationwide maternal health programme that targets both demand- and supply-side factors on the nutritional status of children under five years old whose mothers were potentially exposed to the programme. We employed a difference-in-differences approach by matching programme beneficiary facilities to the districts and communities where households reside. The data are drawn from the 2008, 2013, and 2018 rounds of Nigeria's Demographic and Health Surveys (DHS), comprising responses for approximately 120,000 children. Our findings reveal a significant increase in child dietary diversity, particularly in districts with two beneficiary facilities, suggesting stronger effects with expansive programme implementation. Additionally, we observed positive effects on children's consumption of various nutritious foods for those children in districts with two beneficiary facilities. This study investigates a potential mechanism by which expanding access to healthcare facilities, through funding two clinics per district, may contribute to improved child dietary diversity. Our findings suggest that, unlike districts with one beneficiary facility, those with two funded clinics have a higher likelihood of women engaging in work outside the home and earning cash for it. As shown in the analysis, this mechanism is likely due to easier access to health facilities and better contact with health officers, which facilitate quicker reintegration into the labour market for mothers after childbirth and, in turn, could lead to better maternal earnings and potentially enable a more diverse diet for children. The findings suggest that SURE-P's expansive implementation strengthens child nutrition outcomes and supports maternal economic empowerment. In areas with multiple SURE-P facilities, increased access to healthcare enables mothers to reintegrate into the labor market more quickly, facilitating cash income and fostering a reinforcing cycle of improved child dietary diversity and economic benefits for families. This highlights the potential of scaling such programs to maximize both health and economic outcomes in similar contexts.

1. Introduction

Improving maternal and child wellbeing remains a significant policy priority in many developing countries. Compared to their counterparts in developed countries, women in developing countries typically experience higher average pregnancy rates, which exposes them to a higher lifetime risk of death during pregnancy and childbirth (Gordillo-Tobar et al., 2017). Addressing this issue necessitates targeted health interventions, particularly for women in developing countries, where structural and institutional barriers further impede access to healthcare services.

Recent studies (such as Okoli et al., 2014; Cooper et al., 2019; Gandhi et al., 2021; Cygan-Rehm and Karbownik, 2022) show that interventions aimed at improving maternal health result in positive outcomes for both the directly affected women and their children. These policies can take different forms, from both supply- and demand-side initiatives, which tend to matter in determining child wellbeing (Cooper et al., 2019; Okeke and Abubakar, 2020; Cygan-Rehm and Karbownik, 2022). For

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example, on the one hand, scaling up the demand-side initiative has been shown to be potentially significant in improving child survival rates in Nigeria, with an annual reduction of 85,000 child mortality (Okeke and Abubakar, 2020). On the other hand, there is evidence that supply-side interventions, such as providing mothers with health-related information and supplying health officers to underserved locations, have a significant impact on child wellbeing (Okeke, 2023; Levere et al., 2024). These studies argue that these interventions serve a dual purpose: while they are primarily intended as health interventions to enhance maternal health, they also act as mechanisms for transferring knowledge and norms related to improved investment in child wellbeing.

In this study, we investigate the effect of a nation-wide and extensive health policy initiative in Nigeria that targets different sectors of the economy, including healthcare service delivery and infrastructural improvements. The Subsidy Reinvestment Programme in Nigeria, which began between 2012 and 2015, targets interventions aimed at improving healthcare for pregnant women by bolstering the provision of health services and fostering demand for such services. The program selects facilities within communes across districts in Nigeria's 36 states based on predetermined criteria. These facilities receive comprehensive support, including the supply and renovation of health infrastructure, equipment, staffing, and essential drugs. Additional supplementary measures promoted by the program include cash transfer and community awareness campaigns through targeted outreach efforts in specific communities and clusters of health facilities, while emphasizing the importance of both pre- and post-natal care (Dias et al., 2016).

We leveraged the spatial and temporal differences in the implementation of the programme between 2012 and 2015 to investigate its impact on the nutritional intake quality of the children of beneficiary mothers. Specifically, we ask whether the programme (if expansively implemented) is associated with improvement in the nutritional intake of children with birth years that coincide with the programme implementation period (cohort children), whose mothers were potentially exposed to the programme's benefits.

Our empirical analysis employs a difference-in-difference design, where districts with SURE-P-supported facilities serve as the treated districts. Furthermore, we distinguish between districts with one SURE-P-supported facility and those with two, with the intention of understanding the effect of the program's expansive coverage. Using data from three rounds (2008, 2013, and 2018) of the Demographic and Health Surveys (DHS), we compare the nutritional outcomes of children born after the onset of SURE-P implementation with those born before implementation. In this setup, children within the same cohort tend to share similar characteristics, but for the simultaneous implementation of SURE-P across locations in Nigeria. More so, our empirical analysis supports the plausibility of the parallel trend assumption and mitigates concerns about differential trends in periods prior to SURE-P implementation.

Our findings show a significant improvement in the nutritional outcomes of cohort children in districts with multiple SURE-P beneficiary facilities. This result aligns with evidence from developing countries that highlights the effectiveness of expanded health program coverage (Benyoussef and Christian, 1977; Okeke, 2023). This literature demonstrates that increased coverage of health services can mitigate geographic and structural barriers to access for underserved communities (Benyoussef and Christian, 1977; Druetz et al., 2017). Our results support this claim by showing that the positive effects of SURE-P implementation are observed only in districts with multiple beneficiary facilities.

While we theoretically argue that the implementation of SURE-P includes other factors that could benefit mothers and lead to improvements in child nutritional outcomes, especially in locations with extensive coverage, our empirical analysis identifies the labor market channel as the most credible mechanism explaining the results. For example, the SURE-P rollout includes cash transfers to women to directly encourage maternal use of health services in beneficiary facilities (Onwujekwe et al., 2020). These cash transfers were given to pregnant women in all districts who utilized the services in beneficiary facilities. Other factors, such as promoting health information awareness (Okoli et al., 2014), improving health facility infrastructure (Chukwuma et al., 2019), and using SURE-P funds to fund improvements in transportation infrastructure (Atakpa, 2016), could also lead to better health service delivery for women and community commerce expansion. However, we could not confirm these mechanisms due to data limitations. Nonetheless, our analysis highlights a positive labor market effect in districts with extensive SURE-P coverage. We further confirm that this effect is likely due to improved contact with health professionals and access to health facilities in districts with multiple beneficiary facilities, which may facilitate faster reintegration of women into the labor market. This, in turn, could lead to higher maternal earnings (Molland, 2016; Heath and Tan, 2019) and potentially enhance child nutritional status.

This paper is related to existing research in the health policy literature that focusses on the role of expansive implementation of health programmes in improving maternal and child health and well-being. Benyoussef and Christian (1977) provide country-specific case studies, while Bornemisza et al. (2010) note that promoting access to health services among vulnerable populations requires expanding coverage, particularly in settings where the government is unwilling and/or incapable of delivering basic services to their population. Similarly, Chou et al. (2014) show that the expansion of Taiwan's national health insurance program has positive health impacts, while Gandhi et al. (2021) note that insufficient population coverage is an important factor for the success of health programmes in developing countries.

Our results are a robust contribution to the literature, specifically focussing on the connection between expansive health intervention coverage, maternal outcomes, and child wellbeing. The literature remains inconclusive, with some studies arguing that encouraging outcomes may follow increased access to and use of interventions provided to mothers, while others argue that the complementarity of service quality determines the improvements in outcomes (see Gebremedhin et al. (2022) for a systematic review of this debate). We also link our findings with the vast literature that has examined the connection between the implementation of the specific programme that we focus on (SURE-P) and different outcomes. For example, while Ezumah et al. (2022), Grepin et al. (2022), and Ogu et al. (2023) focused on the general impact of the implementation on maternal health-seeking behaviours and service utilization, Atakpa (2016) and Chukwuma et al. (2019) considered effects on infrastructural development and political trust in Nigeria. Our paper builds on this literature by focussing on the extent to which a more expansive implementation of the programme can significantly impact child outcomes.

We also link our findings with the vast literature in health and economics, which has identified that maternal health programs have generational health and wellbeing consequences. These studies have identified that health and social programs that target maternal wellbeing also have a downstream effect on the health and social outcomes of the beneficiary women's children (Khanani et al., 2010; Okeke and Abubakar, 2020; Cygan-Rehm and Karbownik, 2022; Okeke, 2023). While previous research has established this link, the role of program intensity—measured by coverage in this study—in determining child wellbeing remains unexplored. Our findings show that program coverage plays a crucial role in enhancing child outcomes, especially in contexts where access to maternal health services is limited.

Our study is notable for its focus on child nutritional outcomes resulting from maternal access to healthcare. This is particularly relevant in a context with one of the world's highest burdens of stunted children, where child malnutrition is the leading cause of mortality among children under five, accounting for 45 percent of all deaths in this age group (UNICEF, 2021). Among rural residents and the poor, the target population of the SURE-P mandate (Amakom, 2013; National Planning Commission, 2013; Onwujekwe et al., 2020; Ezumah et al., 2022), the situation is even more dire. Children in rural locations are more stunted (40% compared to 27% in urban areas), severely stunted (22% in rural areas and 10% in urban ones), and those from the poorest households are three times more likely to be stunted relative to those from wealthier households (National Population Commission & ICF International, 2014; USAID, 2018).

The recent work by Leroy et al. (2012), who provided a theoretical framework for how women-targeted health and social programs in Latin America influence child nutrition through their impact on women's agency, most closely relates to our paper. Our study extends this research by examining the effects of a different type of health and social program, SURE-P, on child nutrition in Nigeria. We contribute by delineating program effects based on coverage and comparing districts with one and two beneficiary facilities. Importantly, we assess impacts on both overall dietary diversity and the consumption of specific micronutrients—animal source food, fruits and vegetables, green leafy vegetables, other fruits and vegetables, and vitamin A-rich fruits and vegetables. These micronutrients are critical for child development but are often deficient in sub-Saharan African diets (Ickowitz et al., 2014; Efobi, 2024). Therefore, apart from the academic innovation of our approach, these detailed considerations of nutritional outcomes could further be relevant for policy.

2. Study context

2.1. SURE-P implementation

This study is carried out in Nigeria, Africa's most populous country, with an extremely high maternal mortality rate in Africa (1047 deaths per 100,000 live births), third to South Sudan (1223 deaths), and Chad (1063 deaths) based on the 2023 World Health Organisation report (WHO, 2023). Several factors contribute to this high maternal mortality rate, including a shortage of trained midwives, low-quality health clinics, high healthcare costs, and limited awareness of the importance of prenatal care and delivery assistance from skilled health workers (Dias et al., 2016).

In January2, 012,[1] the Nigerian Federal government began to implement the Subsidy Reinvestment and Empowerment Programme Maternal and Child Health Project (SURE-P), utilizing the removal of subsidies on petroleum to bolster the health system throughout districts in Nigeria with the goal of decreasing maternal and newborn mortality rates. The SURE-P program aimed, among others, to transform the health system in Nigeria by focussing on two critical components: enhancing the supply and demand for maternal health services. This involved improving infrastructure, staffing, and supplies at 1000 targeted public primary healthcare facilities (PHCs) and their catchment areas, spread across Nigeria's 36 states and the Federal Capital Territory. Additionally, communication initiatives were implemented to raise awareness about the importance of prenatal care and skilled delivery assistance; there was the implementation of a conditional cash transfer (CCT) scheme targeting pregnant women in rural and underserved areas; and there were significant investments in improving transportation infrastructure (Amakom, 2013; Okoli et al., 2014; Atakpa, 2016).

To elaborate further, the health-supply-side component of the program prioritized enhancing health services at facilities by recruiting, training, and deploying skilled midwives, community health extension workers, and village health workers to support health service activities at the designated SURE-P facilities. Additionally, the program made investments in infrastructural development within these facilities, which included enhancing the supply of medicines, consumables, and other essential commodities to provide quality maternal and child health services. Upgrading available infrastructure, such as improving clean water supply and renovating health facilities, was also a key focus. There were no restrictions on who did or did not benefit from these improvements to the health facilities.

On the demand side, communication activities were employed to drive behavior change and promote maternal health service utilization. Other areas of demand creation include the development, printing, and deployment of advocacy kits aimed at traditional and religious leaders, policymakers and implementers, lawmakers, traditional birth attendants, health service providers, ward development committees, media executives, family members, and nongovernmental organizations, with the goal of promoting program ownership and generating service demand (USAID, 2014). A conditional cash transfer scheme was implemented, offering up to 5000 Naira (equivalent to 30 US dollars) directly to pregnant women, with adjustments based on the number of services utilized at the beneficiary health facilities. The objective was to incentivize affected women, including pregnant women and those in pre- and post-natal stages, to avail themselves of services at these facilities. Cash incentives were provided to pregnant women who registered for antenatal check-ups, delivered at the beneficiary health facilities, and took their newborns for the first series of vaccinations (Onwujekwe et al., 2020).

The state governments selected nine to sixteen beneficiary facilities based on specific criteria. These included being situated in rural areas, having a population catchment of over 10,000 residents, offering maternal and child health services around the clock, and possessing essential equipment and basic infrastructure like clean water, power supply, and sewage disposal (Chukwuma et al., 2019). Once a state government nominated a facility, demand creation activities such as communication campaigns and conditional cash transfers (CCTs) began alongside supply-side enhancements (improvements in staffing, infrastructure, and commodities). The selection criteria were established to address the unique service delivery needs in rural Nigeria, where access to basic healthcare services differs significantly from urban areas, as is common in many developing countries (Menashe-Oren and Stecklov, 2018).

2.2. Anecdote of SURE-P's success

There is quantitative and qualitative evidence that reflects the effectiveness of the SURE-P. For instance, SURE-P received about 6 percent of the total federal budget between the 2013 and 2014 fiscal years. The programme has received other forms of financial support from the World Bank, including the USD 500 million Saving One Million Lives Initiative, and has reached about 1250 facilities.

Other success stories include the deployment of over 11,000 trained health workers to various facilities, increased renovations to existing health facilities, and the construction and expansion of staff accommodation to support staff retention. Additionally, qualitative research by Holmlund and Crawford (2016) finds that mothers in the catchment areas were 12 percentage points more likely to receive skilled birth attendance than they would have been in the absence of SURE-P.[2]

In terms of grassroots engagement, SURE-P involved the recruitment and training of ward and village health workers to improve interaction between mothers and trained health workers. In 2012, about 6300 new health workers were recruited, with additional recruitment of about 2400 workers in 2013 (National Planning Commission, 2013). The engagement of host communities through the ward development

[1] The program was between 2012 and 2015.

[2] The authors also find that, although skilled birth attendance increased, antenatal care was unchanged.

committees (WDCs) and recruitment of indigenous village health workers (VHW) promoted ownership of the program and stimulated service demand creation.

As previously mentioned, the SURE-P program has two critical objectives: enhancing access to maternal healthcare by promoting deliveries in health facilities and improving infant health outcomes (Dias et al., 2016; Holmlund and Crawford, 2016). While causality cannot be established at this stage,[3] Fig. 1 offers valuable insights into achieving the first objective.

The figure compares the average number of home deliveries in areas with and without SURE-P facilities during the pre-program period (2011) and the post-program period (2013). The figure highlights a significant decrease in the average proportion of women delivering at home in areas with SURE-P implementation during the post-implementation period, with the decline being twice as pronounced as in non-SURE-P locations. Fig. 2 illustrates that the proportion of women receiving antenatal care during their pregnancies in potential SURE-P locations (government hospitals or health centers) increased nearly twice as much as in non-SURE-P locations.[4] This stylized increase in hospital births and antenatal care visits is also corroborated by the government report. For example, the report shows a 32% increase in antenatal visits from baseline, and the number of hospital births also increased in locations with SURE-P (National Planning Commission, 2013).

While this section presents broad patterns of success, more detailed evidence comparing outcomes across locations with varying levels of SURE-P implementation (e.g., places with one versus two clinics) provides deeper insight into the programme's impact. These comparisons, particularly regarding maternal healthcare access and contact with health professionals, are discussed later in Section 6B, where the impact of varying SURE-P coverage is explored in greater detail.

Despite these success stories, one element remains unknown: whether the improvement in access to maternal healthcare in the pre- and post-natal period is associated with an improvement in the nutritional outcomes of beneficiary mothers' children. In addition, is such an association dependent on the extent of SURE-P coverage, i.e., whether the effect is consistent regardless of the number of beneficiaries in a specific location? The subsequent section will explore these issues in detail and clarify the underlying mechanisms of these effects.

3. Description of data

In answering the research questions, we used data from the 2008, 2013, and 2018 rounds of Nigeria's Demographic and Health Surveys (DHS). As this data is publicly available, de-identified, and adheres to ethical standards with prior approval, additional ethical approval was not required for its use.

This dataset provides comprehensive information on the nutritional intake of children under 5 years old, as reported by surveyed women, as well as demographic details about the women themselves. Importantly, the DHS data includes spatial identification of the household locations of the respondents, which allows us to match those locations with the locations of the SURE-P facilities using the GPS coordinates.[5]

3.1. Child nutrition

We calculate dietary diversity scores for children under five based on the number of food groups[6] consumed in the previous day or night, as reported by their mothers in the 2008, 2013, and 2018 DHS surveys. We follow the FAO and FANTA guidelines for defining food groups (FAO-FANTA, 2007), similar to other studies that consider this approach in measuring child nutritional intake (Ickowitz et al., 2014; Efobi, 2024). We count the categories of food intake and derive the standardized value as the primary outcome variable for the analysis. We standardize this indicator to interpret the coefficient estimates from our regression analysis as the change in standard deviation units, providing a more informative understanding of the effect's magnitude, particularly because we are considering changes across groups. As a result, the standardisation puts the primary outcome variable on a common scale (with a standard deviation of 1) for easier comparison.[7]

We also measured distinct indicator of nutritional intake, as the probability of the child consuming (a.) fruit & vegetables, (b.) vitamin A-rich fruits & vegetables, (c.) green leafy vegetable, (d.) other fruits & vegetables, and (e.) animal source-food consumption. These indicators are relevant considering that dietary diversity alone may not fully capture the nutritional needs of children, especially in regions like Sub-Saharan Africa where certain micronutrients are often lacking in diets (Ickowitz et al., 2014; Efobi, 2024).

While dietary diversity assigns equal weight to each food category, not all food groups contribute equally to a child's nutrition (Efobi, 2024). For instance, inadequate consumption of fruits and vegetables, despite being crucial sources of essential micronutrients like vitamin A, vitamin C, folate, iron, and phytochemicals, remains a significant global health concern (Ickowitz et al., 2014). Additionally, vegetables provide essential minerals such as iron and calcium, while animal-sourced foods are rich in iron, zinc, vitamin A, and vitamin B12, vital for growth and cognitive function (Neumann et al., 2003). Low intake of these foods can lead to protein deficiency and reduced bioavailability of many

[3] Several other factors could explain these outcomes, including population density, topography, or typical travel time to and from the facility.

[4] Based on the data, an average of 63% of the women in the study had home births (compared to the 2013 DHS national average of 63.1% and 76.9% in rural areas). Additionally, only about 12% of the sample visited antenatal care at government hospitals or health centers (compared to the 2018 DHS national average of 25.3% for those who visit doctors for ANC and 14.7% in rural locations). These national statistics are from the National Population Commission & ICF International, 2014. Notably, the findings from our study are similar to the trends observed in the 2018 DHS survey.

[5] One can read the DHS guideline on the methodology for the DHS GPS data collection here https://dhsprogram.com/pubs/pdf/DHSM9/DHS_GPS_Manual_English_A4_24May2013_DHSM9.pdf. To ensure respondent confidentiality, the DHS employs random displacement of GPS latitude/longitude positions in all surveys. Urban clusters are subject to a minimum of 0 and a maximum of 2 km of error, while rural clusters have a minimum of 0 and a maximum of 5 km of positional error. Additionally, 1% of rural clusters are displaced by a minimum of 0 and a maximum of 10 km. However, these displacement parameters do not pose concerns for our identification purposes, as our unit of variation is at the district level, encompassing a much larger geographical area that accommodates for any DHS displacements.

[6] That is, we followed the Food and Agricultural Organization (FAO) and the Food and Nutrition Technical Assistance Project (FANTA) guidelines for creating dietary diversity scores based on the following 14 food groups: cereals; vitamin A–rich vegetables and tubers; white roots and tubers; green leafy vegetables; other vegetables; vitamin A–rich fruits; other fruits; organ meat; flesh meat; eggs; fish; legumes, nuts, and seeds; milk and milk products; oils and fats; and we included condiments. We included condiments because some foods are consumed as condiments in this study's context, including, for example, dried fish and some local condiments made from fermented seeds or nuts, most often African locust bean seeds or groundnuts (Becquey et al., 2009; Agada and Igbokwe, 2015; Olabisi et al., 2021). Nonetheless, we show in the robustness checks that the results do not change when computing dietary diversity by excluding condiments.

[7] In a robustness check, we analyzed the effects using raw estimates, and the results consistently showed the same direction of effects while remaining statistically significant.

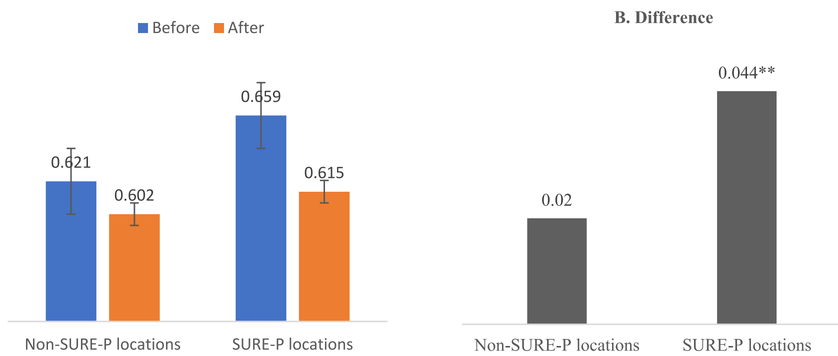

Fig. 1. Proportion of births at home across locations for periods 2011 and 2013.
Note: The period selected, 2011 and 2013, was chosen to illustrate changes in key SURE-P objectives before and after the program's implementation. The presented values represent the average, and the "difference" indicates the absolute difference in mean between the two periods (before and after). These values are derived from the two-sample *t*-test with equal variances. ** denotes significance at the 5 percent level.

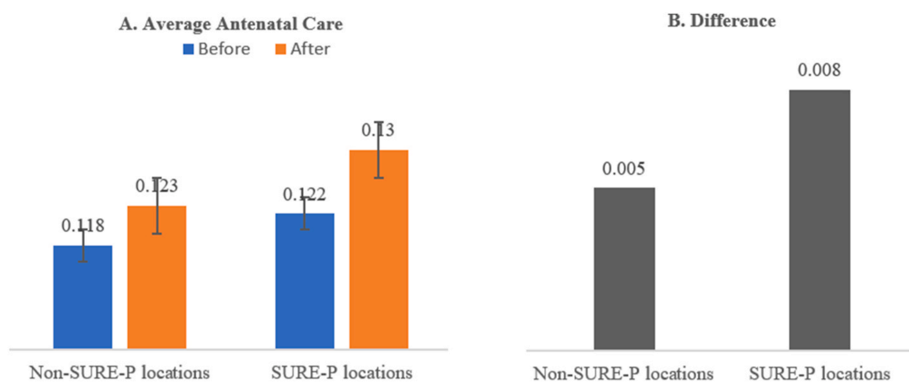

Fig. 2. Proportion of antenatal care in the health centre.
Note: Similar to Fig. 1.

micronutrients. Therefore, considering both dietary diversity and anthropometric outcomes offers a more comprehensive assessment of a child's nutritional status, capturing the variety and quality of their diet and highlighting potential deficiencies or imbalances that may impact overall health and development. We included anthropometric indicators only in the supplementary analysis, as they are not the primary focus of this study.

3.2. SURE-P locations

We obtained the precise addresses and locations of all 1000 primary health facilities that benefit from the Subsidy Reinvestment and Empowerment Programme (SURE-P) from the National Primary Healthcare Development Agency, Nigeria. Relying on this geolocation data, we mapped these selected health facilities to enable us to match households from the DHS to the beneficiary health facilities. To strengthen our analysis of the relationship between SURE-P provision and the social status of beneficiary women, we define SURE-P-affected households or beneficiaries as those residing in communities within the district of the beneficiary health facility.

4. Identification and validity checks

4.1. SURE-P and dietary diversity

To examine the effects of SURE-P on child nutritional outcomes, we estimate the following equation:

$$y_{imlt} = \alpha + \beta_1 SURE\_P_{iml} + \beta_2 Post_t + \beta_3 SURE_P \times Post_{ilt} + \sigma X_{imlt} + \mathrm{m}_m + \theta_l + t_t + \Omega + \vartheta_{lt} + \varepsilon_{imlt} \quad (1)$$

Where y_{imlt} is the outcome of interest. The primary outcome variable is dietary diversity, which is the standardized score in our regression analysis. Other outcome variables are the probability of the child consuming fruit & vegetables, vitamin A-rich fruits & vegetables, green leafy vegetable, other fruits & vegetables, and animal source-food consumption for child *i* born to mother *m* who resides in district *l*, who was surveyed in year *t*, Table 1 presents the summary statistics for the primary outcome variable and the other indicators of child nutritional outcomes. The average child in the sample consumed about 3 food categories in the day or night preceding the survey. In terms of the nutrients consumed, the information from the Table also shows that most of the children consumed animal source food (about 45 percent), fruits and vegetables (about 38 percent), and green leafy vegetables (about 29 percent). Only about 15 percent of the sample children consumed other fruits & vegetables and a small proportion (8 percent) consumed Vitamin A-rich fruit & vegetables.

Our main measure of exposure to health service provision is "SURE_P″, which is an indicator that equals 1 if a district has at least one SURE-P facility. We also explored the indicator that reflects whether the district has one SURE-P facility (a district where there is one SURE-P

Table 1
Summary statistics.

	Full Sample	Control	SURE-P	Districts with one SURE-P (152 districts)	Districts with two SURE-P (105 districts)
Dietary diversity*	3.071	3.033	3.155	3.304	2.832
Fruit & vegetables = 1	0.384	0.380	0.395	0.399	0.367
Vitamin A-rich fruit & vegetables = 1	0.080	0.075	0.091	0.099	0.072
Green leafy vegetables	0.288	0.284	0.296	0.294	0.270
Other fruits & vegetables	0.147	0.144	0.155	0.178	0.131
Animal source-food	0.453	0.454	0.451	0.462	0.400

Note: For this summary statistics we do not provide the standardized value of the primary outcome (dietary diversity), since the purpose is to show a mean description of this variable.

facility – 152 districts) and a measure of expansive implementation in health service provision, reflecting a district hosting two SURE-P facilities[8] - 105 districts.

Unlike other related studies that rely on the distance cutoff as a measure of SURE-P exposure (see Onwujekwe et al., 2020; Grepin et al., 2022; Ezumah et al., 2022), our measure allows us to observe the effect of expansive exposure using the number of SURE-P facilities in the district. Table 1 further describes mean statistics of the outcome variables across the different SURE-P status.

$Post_t$ is a binary indicator that captures cohorts with birth years between 2012 and 2015. This period is when the SURE-P programme officially began and ended in Nigeria. We focus on children born between 2012 and 2015 because it allows us to compare the dietary diversity of children who were potentially exposed to the program in utero or during their early years with those born outside this timeframe (those with birth years before 2011, whose mothers did not benefit from the SURE-P).

This specification includes a set of unrestricted within-community dummies, denoted by θ_l. It captures unobserved variations that are fixed across communities. Adjusting for this fixed effect at a lower level (community level) than the level of our treatment (district level) is particularly relevant for three reasons: first, community fixed effects capture between-community differences in time-invariant characteristics, such as distance to a health facility. These characteristics do not change over time within a location. Second, community-level effects are nested within our treatment level (district), which allows us to isolate the direct effect of the program at the district level.

Third, following the programme rollout that targets communities within district, it is reasonable to assume that there are community-level factors that could influence our outcome variable and confound the true programme effect. An example is political clientelism at a more local level that may determine the targeting of social program in Nigeria because it is at this level that the representatives of constituent ethnic/cultural groups are organized to represent and protect the interests of such communities (Omobowale, 2006; Ọmọbọwale and Olutayọ, 2010; Croke and Ogbuoji, 2024). Therefore, including fixed effects at the community level allows us to control for any community-specific effects that may influence our outcome variable, while still estimating the treatment effect at the district level. Hence, it is expected that our estimated treatment effect will be void of any bias by unobserved community-level factors. As will be discussed in the result section, the results are consistent even when we include district-level fixed effects, although our main location variable (SURE_P is dropped because of multicollinearity).

We additionally include mother's fixed effect 'η_m' to capture fixed commonality across children from the same mothers especially when certain characteristics are unique to children of the same mother. The survey-year t_t fixed effects account for fluctuations unique to specific period, such as price changes that varies over specific dates in Nigeria, corresponding with the DHS survey year. We also include community × year of birth fixed effect 'Ω' to capture unobserved fluctuations peculiar to the community and the year of birth of the child, e.g. violent conflict specific to communities and coinciding with the year of birth of the child.

Equation (1) includes district-specific time trends, $\vartheta_{l\tau}$, that allow our SURE-P and non-SURE-P districts to follow different trends over time. These trends may be influenced by factors such as labor-market cycles, conflict, or seasonality in agricultural production, all of which can impact food costs, production, and availability at the individual and household levels. The regressions also include a comprehensive set of control variables, summarized in Table A1. These carefully chosen controls include the woman's average age (32 years), the average age of the current spouse (42 years), educational attainment (primary school completion for 21% of women and 19% of spouses), presence of other wives in the household (37%), rural residence (72%), household size (8 members), and the average number of children under five years old (2 children). Errors are clustered at the community level to correct for heteroskedasticity and serial correlation at this localized level.[9]

4.2. Identification and validity checks

To estimate SURE-P's effect, we matched individual-level data from the DHS with the SURE-P district using their GPS coordinates. We employed the difference-in-differences (diff-in-diff) method to analyze the data. This technique isolates the program's effect on dietary diversity by comparing locations with and without the SURE-P program, while accounting for variations based on the birth year of the child.

Noting that the timing of the programme is consistent across locations[10], the treatment in this study is considered at the district level, rather than proximity to the SURE-P facility, as used in other studies (see Chukwuma et al., 2019), for the following reasons. They include a). Primary health care is the responsibility of the district government, which oversees, and funds health facilities involved in primary care. b). As previously discussed, the devolution of SURE-P administration to state and local government through the introduction of village healthcare workers and community health extension workers suggests that the program's distributional effects will be more visible at local administrative levels, regardless of distance to facility. This is due to the lack of a clear mechanism for distinguishing between locations with and without the programme. As a result, considering the impact at the local administrative level (in our case, district) allows us to differentiate between locations with and without the SURE-P facility.

Fig. 3a shows districts categorized by SURE-P program exposure: treatment (having at least one beneficiary SURE-P facility) and control (no SURE-P facilities). It is essential to note that there are distinct

[8] About three percent of the districts have more than two SURE-P facilities. Therefore, we focus our analysis on districts with one or two SURE-P facilities to maintain consistency within the model and to prevent multicollinearity issues that could arise from including additional treatment variables. While we do not report the results for districts with three or more SURE-P facilities due to limited statistical power, we conducted the analysis, and the findings were not statistically meaningful.

[9] This clustering accounts for correlation in the error terms among children residing in the same district and experiencing similar shocks.

[10] The timing referred to here is the timing of the rollout (2012–2015) and we do not have any record showing the exact timing of specific aspects of the programme, such as the rollout of additional health workers etc.

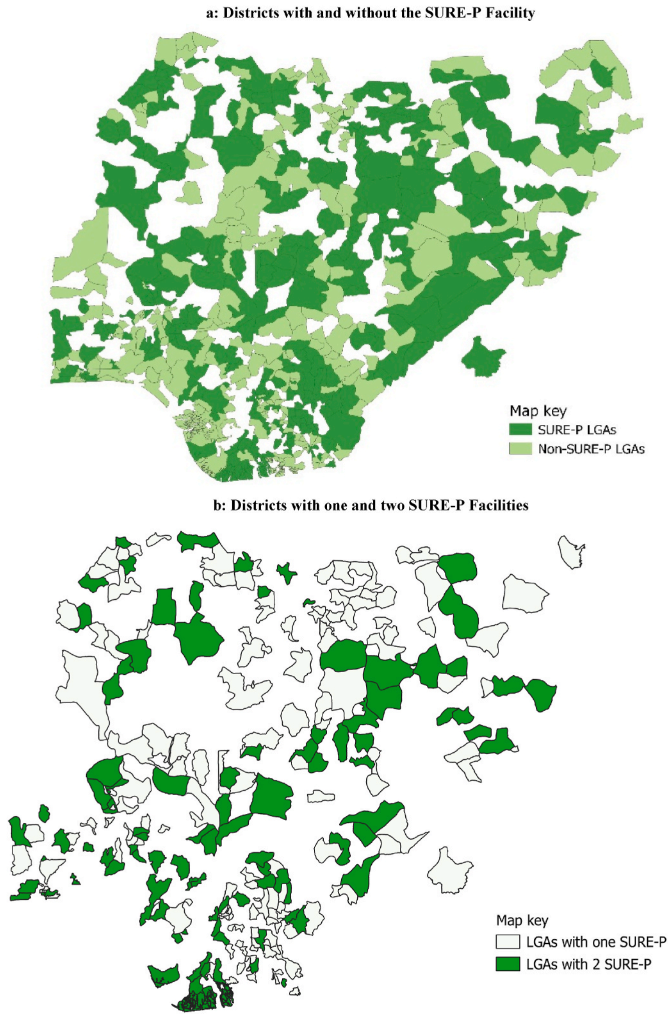

Fig. 3a. Districts with and without the SURE-P Facility
b: Districts with one and two SURE-P Facilities.

demarcations between districts with DHS clusters and SURE-P (treatment) and districts with DHS cluster but no SURE-P (i.e., control). Such precise delineation is critical for our identification to demonstrate distinct differences between locations with and without SURE-P, allowing us to estimate the effect of the SURE-P programme on the outcome variables of interest. The Figure further highlights the significant variation in SURE-P locations across the country's districts, which are nearly evenly distributed. Therefore, for the period of our analysis, the districts do not switch quasi-randomly between treatment and control from year to year. Fig. 3b displays districts by their level of SURE-P program exposure, indicated by the number of beneficiary facilities.

Two key assumptions underlie our difference-in-differences analysis: The first is selection bias. We assume that the locations chosen for the SURE-P program (treatment group) are comparable to those without the program (control group) in all observable ways besides receiving SURE-P. In simpler terms, any pre-existing differences that could affect child dietary diversity (the outcome variable) should not be systematically linked to the selection of SURE-P locations. The second is parallel trends assumption. That is, before the SURE-P program began in 2012, the primary outcome variable, child dietary diversity, should have exhibited similar trends in both treatment and control groups. Ideally, these trends should be parallel in the pre-intervention period. The next sub-sections clarify these points.

Assumption 1. Orthogonality of SURE-P location to the Error Term

Despite the stability of the district's treatment and control status, the selection of the SURE-P facility location (including locations with only one or two facilities) may be quasi-randomly determined, since the criteria for selection are subject to government nominations based on clearly defined criteria (Amakom, 2013; Chukwuma et al., 2019). Therefore, our OLS framework in Equation (1) requires an important identification assumption – that is, conditional on the district-time trends, community and year of birth fixed effect, year, and (and other observed district characteristics), the siting or selection of the SURE-P facility in such district must be orthogonal to the random error term. This assumption is represented in equation (2), as follows:

$$E(SURE\_P_{ls} \times \varepsilon_{ilst} | \vartheta_{lt}, \theta_l, \delta_s, \Omega, t_t) = 0$$

We conduct the following placebo tests to evaluate the plausibility of this assumption, by asking: do relevant demographic and geographic factors vary evenly between SURE-P[11] and non-SURE-P districts? To test this, we first clarify whether individuals (i.e., mothers) that are in SURE-P districts are appropriate counterfactual for those located in non-SURE-P districts. To test this, we estimate simple regressions of the relationship between SURE-P district status and the individual demographic characteristics, X_{ilst}, of mothers in the districts. The individual characteristics, X_{ilst}, is included in equation (1) as our outcome to see if these characteristics differ significantly SURE-P (treatment) and non-SURE-P (control) districts.

We estimate this correlation for all women in the DHS sample and for the subset with infants (those included in this study's analysis). The results in (Table A2) of Appendix A show no significant differences between the characteristics of the women, their spouses, and the household in SURE-P and non-SURE-P districts. To see if time-varying geographic characteristics such as total population (including the population of under-5 children and population density), economic development (measured by night-light composite) temperature,[12] disease incidence (measured by malaria prevalence), and previous access to health programs,[13] differ significantly between SURE-P and non-SURE-P districts, we estimate equation (1) with these geographic characteristics as outcomes. The findings in Table A3 of Appendix A indicate that there are generally no significant variations in the time-dependent geographical features between SURE-P and non-SURE-P districts, except for a significant positive association observed between areas with two SURE-P facilities and population density.[14]

In addition to the direct empirical evidence from the data, Nigeria's political structure supports the notion of reasonable exogenous district selection. The public health administration framework in Nigeria aims to prioritize local governments in managing maternal health programmes. That is, the primary health care duty is at the district level, which oversees and administers funds for health institutions. Nonetheless, the state government's pre-determined biases, for example, could potentially systematically taint the selection of beneficiary and non-beneficiary districts, given the political implications of these choices, especially considering the upcoming election two years after the program's launch. The only potential concern may be in the selection of beneficiary facilities, as some local governments may prioritize facilities

[11] This also connotes districts with one or those with two SURE-P facilities.

[12] Precipitation and temperature may correlate with seasonality of diseases and its transmission (Polgreen and Polgreen, 2018) and could influence the decision to select health facility in a location over others.

[13] This measure shows previous access to health programs, measured by the average number of people in the community who slept under an insecticide treated net the night before they were surveyed. Access to ITNs is mostly provided by donors in the majority of SSA countries (Desmon, 2020) and acquiring bed nets is unattainable in this context, since only affluent households do so from informal markets and donor-supplied nets that have leaked (Olapeju et al., 2019).

[14] We further explore this issue in the result section.

based on predetermined prejudices, such as clientelist gains from placing facilities in ethnic or political strongholds (Habyarimana et al., 2007; Posner, 2017; Harris and Posner, 2019). For our study, we do not see this as a problem because the treatment status is at the district level rather than the local community level, where these issues may be more common. Nonetheless, we can readily account for this in a robustness check by capturing indices of ethnic fractionalization at the state level. Assuming this is a relevant issue in our identification, we anticipate that controlling for the extent to which a state is fractionalized across various dimensions can easily absorb these concerns in our analysis (see robustness tests for additional explanation and findings).

Assumption 2. Pre-trend in Primary Outcome, Other Policies, and Shocks

A violation of this assumption would occur if districts with the SURE-P were systematically more (less) different in child dietary diversity outcome or if changes over time in this outcome were systematically different from other non-SURE-P districts. To check the validity of this assumption, we compute district-level averages of the primary outcome variable. Fig. 4 shows that the primary outcome variable exhibited a similar trend for the two locations in periods before the commencement of the SURE-P in 2012. Likewise, the figure also shows that there is a similar trend in the averages for locations with one SURE-P, those with two SURE-P, and the non-SURE-P locations.

Another potential challenge to our ability to identify the effects of SURE-P is the possibility of a confounding policy shock, such as increased investment in primary health care facilities, occurring simultaneously with the implementation of SURE-P. If such a policy shock occurs, it becomes difficult to discern whether the observed impact is attributable to SURE-P or to other initiatives implemented during the same period. However, it is reassuring to note that there are no significant large-scale health supply initiatives known to have taken place during this timeframe. In fact, the reinvestment of the subsidy was generally perceived as a windfall allocation from the federal government to state governments, intended to enhance the delivery of social services within their respective jurisdictions (Ezumah et al., 2022).

5. Results

5.1. Effect of SURE-P

Table 2 presents the estimates from specification (1), specifically, effect across SURE-P locations. The table displays OLS coefficients alongside standard errors clustered at the community level, enclosed in parentheses. All regression analyses incorporate fixed effects at the community,[15] mother, survey-year, and community-year of birth levels. The primary outcome variable, standardized for this analysis, is dietary diversity. As earlier noted, we prefer this measure because it provides a more informative understanding of the effect's magnitude, particularly because we are considering changes across groups.

The coefficient of interest, denoted as ' β_3', pertains to *'SURE_P × Post,'* capturing the program's implementation effect. Across columns [1] to [6], the estimates consistently show positive associations between the dietary diversity score, individual indicators of child nutrient intake, and the implementation of the SURE-P program. While these estimates do not attain statistical significance at the conventional 1 or 5 percent levels, they suggest a positive relationship between program implementation and improvements in child nutritional intake.

[15] As will be shown in the robustness check, the results are consistent when we include fixed effects at the district level, although the direct effect of the indicator of SURE-P was dropped in this specification. As earlier noted, the context peculiarity with the administration of the SURE-P and other social programs in Nigeria necessitated the need for including fixed effects at the community-level.

Although the estimates lack statistical significance, the point estimates suggest enhancements in the child's dietary diversity and individual nutrient intake indicators following the implementation of the program. The observed point estimate differences in the outcome indicators corroborate this assertion. Specifically, the dietary diversity score in column [1] demonstrated an improvement of 0.006 standard deviations during periods of program implementation compared to non-implementation periods. Similar increases were observed in other secondary outcome measures of child nutritional intake (see columns 2–6).

5.2. Effects by the 'Quantity' of SURE-P beneficiary Facility

Table 3 presents the estimates when considering the treatment indicator, which is the number of SURE-P facilities within the household's district. We categorize these indicators as 'one SURE-P′ and 'two SURE-P′, indicating whether the district has only one or two selected SURE-P facilities. In column 1, the coefficient for 'Two SURE-P × Post' is statistically significant, suggesting a positive improvement in dietary diversity in districts with two SURE-Ps during the post-treatment period. The implication is that SURE-P's effect is more pronounced with extensive implementation. Children in districts with two SURE-P beneficiary facilities show a significant improvement (at the one percent level) in their dietary diversity score of 0.183 standard deviations. These improvements persist across various indicators of a specific child's nutritional intake. For example, estimates from column 2 suggest that children in districts with two SURE-P facilities are significantly more likely to consume fruit and vegetables by 9.5 percentage points. Additionally, they are significantly more likely to consume green leafy vegetables by 7.7 percentage points (see column 4), other fruits and vegetables by 5.1 percentage points (see column 5), and animal source food by 7.8 percentage points (see column 6).

The lack of significant effect that is recorded for the *One SURE-P × Post* relative to the *'Two SURE-P × Post* may suggest that the effect of the programme nutritional intake on affected children is only dependent on the extensivity of SURE-P implementation coverage. This conclusion is consistent with the existing literature on health program implementation in developing countries, particularly in rural areas, where geographic and structural barriers often impede potential beneficiaries from accessing program benefits (Bart et al., 2012; Okeke, 2023). Therefore, by expanding program rollout, these constraints can be effectively addressed, allowing beneficiaries who would hitherto have been excluded due to these constraints to access and benefit from the program. Hence, establishing additional service provision points in such underserved locations with limited access to existing facilities can further enhance program reach and accessibility (see Wools-Kaloustian et al. (2009) for a study showing improvement in healthcare access with expansion of HIV care services in Kenya).

5.3. Validating the results

To affirm the validity of our identification strategy and ensure the robustness of our estimates across various analytical iterations, we present the estimates of equation (1) under different conditions.

First, we checked for the consistency of the results using raw estimates of dietary diversity, instead of the standardized measure. The findings in Panel A of Table A4 (specifically, column 1) suggest that the results are generally consistent with those in Tables 2 and 3 Furthermore, we also exclude condiments as a food category measure in the computation of our dietary diversity variable, and evidence from column 2 of Panel A of Table A4 reveals that the main results in Tables 2 and 3 do not change. In addition, although not reported, we checked whether including the child's age (both the linear and squared terms) in the model altered the results, allowing us to account for both linear and non-linear effects of age. The results are consistent and do not change.

Second, we examined whether the results hold, when we control for those time-invariant unobservable factors that vary by district. As noted

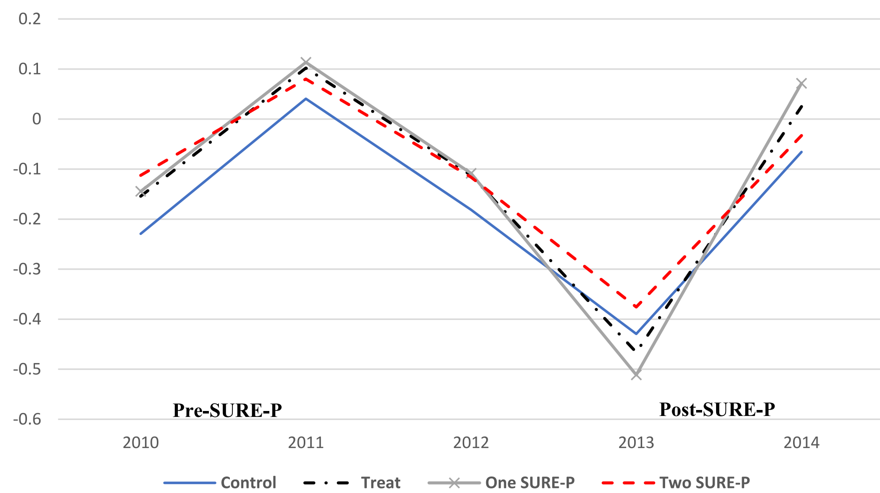

Fig. 4. Dietary diversity averages (standardized) over the years of birth of the child.
Note: This figure provides a preliminary look at how average dietary diversity (standardized) might vary across birth cohorts and program exposure (control, treatment, and locations with one or two program beneficiaries). The data comes from the primary data source - Nigeria Demographic and Health Surveys (DHS). We focus on children born immediately before and after the 2012 SURE-P program launch. By comparing dietary diversity across these groups, the figure allows us to visually explore potential associations between birth cohort, program exposure, and dietary outcomes. Notably, it helps assess whether pre-program trends were similar across groups, which is crucial for interpreting the program's impact in the subsequent tables. Following this figure, the subsequent tables present the formal analysis of the program's effect on dietary diversity using regression models. These models account for various confounding factors and provide more robust evidence for the program's impact.

Table 2
SURE-P and child dietary diversity.

	Dietary diversity (standardized)	Fruit & vegetables	Vitamin A-rich fruit & vegetables	Green leafy vegetables	Other fruits & vegetables	Animal source-food
	[1]	[2]	[3]	[4]	[5]	[6]
SURE_P	0.021 (0.032)	0.025 (0.014)	0.002** (0.000)	0.018 (0.014)	0.010 (0.010)	−0.003 (0.014)
SURE_P × *Post*	0.027 (0.042)	0.029 (0.021)	0.010 (0.010)	0.027 (0.018)	0.014 (0.014)	0.006 (0.021)
R-squared	0.382	0.293	0.284	0.298	0.303	0.348
N	120,604	120,604	119,926	120,023	119,988	120,604

Note: Adjusted standard errors, displayed in parentheses, account for clustering at the "community level." The variable "Post" is a dummy, taking a value of one if the child was born in 2012 or later, coinciding with the implementation period of the SURE-P program. Each regression includes controls for the woman's age, the age of her current spouse, whether the woman completed primary school, whether the spouse completed primary school, whether there are other wives in the household, a rural dummy variable, household size, and the number of children under five in the household. Additionally, fixed effects incorporated into the regression are community-, mother-, survey year-, and the community-year of birth fixed effects. The district-specific trend is also accounted for in the regression. The analysis focuses on children born before 2015. $^{**}p < 0.05$.

Table 3
Expansive SURE-P implementation and child dietary diversity.

	Dietary diversity (standardized)	Fruit & vegetables	Vitamin A-rich fruit & vegetables	Green leafy vegetables	Other fruits & vegetables	Animal source-food
	[1]	[2]	[3]	[4]	[5]	[6]
One SURE_P	0.033 (0.059)	0.046* (0.025)	0.030* (0.015)	0.019 (0.024)	0.034* (0.018)	−0.029 (0.025)
One SURE_P × *Post*	0.001 (0.074)	0.010 (0.036)	0.024 (0.018)	0.005 (0.032)	0.025 (0.023)	0.001 (0.036)
Two SURE-P	−0.093* (0.052)	−0.014 (0.024)	0.000 (0.013)	−0.038* (0.022)	−0.020 (0.015)	−0.041* (0.024)
Two SURE-P × *Post*	0.183*** (0.067)	0.095*** (0.033)	0.018 (0.015)	0.077*** (0.029)	0.051** (0.022)	0.078** (0.033)
R-squared	0.383	0.293	0.283	0.298	0.304	0.350
N	120,604	120,604	119,926	120,023	119,988	120,604

Note: Adjusted standard errors, displayed in parentheses, account for clustering at the "community level." The variable "Post" is a dummy, taking a value of one if the child was born in 2012 or later, coinciding with the implementation period of the SURE-P program. Each regression includes controls for the woman's age, the age of her current spouse, whether the woman completed primary school, whether the spouse completed primary school, whether there are other wives in the household, a rural dummy variable, household size, and the number of children under five in the household. Additionally, fixed effects incorporated into the regression are community-, mother-, survey year-, and the community-year of birth fixed effects. The district-specific trend is also accounted for in the regression. The analysis focuses on children born before 2015. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

Table 4
SURE-P implementation and child anthropometric measures.

	Underweight	Stunted	Malnutrition
SURE_P	0.041 (0.025)	0.015 (0.028)	0.003 (0.030)
SURE_P × Post	−0.021 (0.069)	−0.040 (0.090)	−0.136 (0.086)
R-squared	0.357	0.391	0.399
N	41,907	40,257	40,244
One SURE_P	0.041 (0.044)	−0.041 (0.047)	−0.006 (0.053)
One SURE_P × Post	0.047 (0.160)	0.250 (0.188)	0.104 (0.190)
Two SURE-P	0.082** (0.041)	0.058 (0.045)	0.088* (0.047)
Two SURE-P × *Post*	−0.009 (0.125)	−0.192 (0.137)	−0.149 (0.162)
R-squared	0.357	0.391	0.399
N	41,907	40,257	40,244

Note: Adjusted standard errors, displayed in parentheses, account for clustering at the "community level." The variable "Post" is a dummy, taking a value of one if the child was born in 2012 or later, coinciding with the implementation period of the SURE-P program. Each regression includes controls for the woman's age, the age of her current spouse, whether the woman completed primary school, whether the spouse completed primary school, whether there are other wives in the household, a rural dummy variable, household size, and the number of children under five in the household. Additionally, fixed effects incorporated into the regression are community-, mother-, survey year-, and the community-year of birth fixed effects. The district-specific trend is also accounted for in the regression. The analysis focuses on children born before 2015. $^{**}p < 0.05$; $^{*}p < 0.1$.

previously, there are compelling contextual and analytical reasons for favoring community-level fixed effects over district fixed effects in the earlier analysis. Contextually, the SURE-P implementation targeted community clinics, so focussing on community differences may be more relevant for our analysis than including broader district-level variations. Analytically, the inclusion of district fixed effects would obscure the coefficient of the direct effect of SURE_P. Nonetheless, in this robustness check, we include district fixed effects in this analysis to verify the consistency of our earlier findings. The results from Panel B of Table A4 in the appendix align consistently with the earlier findings presented in Tables 2 and 3

Third, we addressed the issue of ethnic fractionalization, which can impact the distribution or implementation of health programs in Nigeria. To quantify ethnic fractionalization, we utilized Afrobarometer data from rounds 4, 5, and7,[16] which align with the DHS survey rounds used in our analysis. We measured ethnic fractionalization based on individuals' self-reported preference for ethnic identity over national identity. Specifically, we computed ethnic fractionalization as the proportion of the population in specific location who indicated feeling 'only' or 'more' of their ethnic group identity than a Nigerian identity.[17] As a result, locations (states) with a higher proportion of individuals identifying more strongly with their ethnic group may exhibit greater fragmentation along ethnic lines. This ethnic fractionalization could potentially influence program implementation, as ethnic sentiments may play a role in the selection of beneficiary locations within these states. Nonetheless, the results presented in Panel C demonstrate consistent estimates comparable to those in Tables 2 and 3.[18]

The issue of endogenous migration presents another concern. Locations with the implementation of SURE-P or expanded program implementation may attract new residents, which could potentially cause a shock to the local economy or food market (Ruiz and Vargas-Silva, 2015; George and Adelaja, 2022) and thereby impact child nutrition. Such migration shocks could potentially confound the program's estimated effect on child nutrition. To address this concern, we controlled for the migration status of the household by including a binary variable indicating whether the woman/mother has never moved from her current location, as reported in the DHS survey (46 percent of the women). This control helps to account for potential differences in maternal characteristics and experiences associated with migration, which could otherwise bias the estimated impact of the SURE-P program on child nutrition. Again, despite controlling for the migration status of households in the regression analysis, the results remain consistent (see Panel D of Table A4).

Finally, we conduct a placebo test by attributing the period for the implementation of the SURE-P program to 2016, 2017, and 2018, which are obvious periods when the SURE-P program ended. One may argue that although SURE-P ended in 2015, the benefits of the infrastructural investment in SURE-P facilities may persist despite the termination of the program. This argument is valid, but other mechanisms that could impact household income and improvements in child nutrition, such as cash transfers and faster maternal recovery post-birth, may not continue with the termination of the program implementation. Therefore, using periods when the program is no longer in existence as a placebo implementation period will be relevant in verifying the robustness of our initial results. Overall, the results in Tables 2 and 3 remain robust in terms of signs and significance levels (see Panel E of Table A4).

5.4. Effects on other measures of nutritional outcome

In this supplementary analysis, we examine various effects on other measures of nutritional outcomes, including **Underweight:** This indicator reflects low weight-for-age and serves as an indication of moderate to severe malnutrition. Specifically, underweight is defined as weight-for-age falling below −2 standard deviations but not exceeding +2 standard deviations from the reference population. **Stunting:** Stunting reflects low height-for-age and suggests long-term insufficient nutrient intake and/or recurrent infections during the critical period of growth, typically from conception to the age of five. This indicator is measured as height-for-age below −2 standard deviation and the reference are those not above +2 standard deviation. **Malnutrition:** This binary indicator signifies whether a child is underweight, stunted, or wasted.[19] It offers a comprehensive measure of overall malnutrition and is essential for assessing the overall nutritional status of children within the population.

We examine effects on these indicators in Table 4 and the results align (in coefficient signs) with the earlier findings presented in Tables 2 and 3 The results suggest a negative correlation between SURE-P implementation and the likelihood of children experiencing underweight, stunting, or malnourishment, particularly in locations with expanded implementation. However, the lack of statistical significance in some associations, which contrasts with the estimates in Table 3, may stem from the fact that our measure of nutrition intake or food diversity

[16] This round of data was collected in 2017. Analysis indicates that the averages across locations did not exhibit significant variations over the years – i.e., between rounds 4, 5, and 7. Therefore, we do not anticipate that the difference in time frame between round 7 and the DHS 2018 survey will pose a challenge to our analysis.

[17] Specifically, the Afrobarometer poses the following question: "Let us suppose that you had to choose between being a Nigerian and being a [Respondent's ethnic group]. Which of the following statements best expresses your feelings?" Respondents can choose from the following options: "I feel only Nigerian", "I feel more Nigerian than [Respondent's ethnic group]", "I feel equally Nigerian and [Respondent's ethnic group]", "I feel more [Respondent's ethnic group] than Nigerian", and "I feel only [Respondent's ethnic group]".

[18] The results remain consistent even after controlling for state fixed effects, which may capture variations in political competition affecting health program implementation (Croke and Ogbuoji, 2024). This specific result is available upon request but was not reported due to space constraints.

[19] Wasted is defined if the weight-for-height standard deviation is below −2 but not above +2.

is more sensitive to short-term dietary changes induced by the program. These measures directly capture food intake and variety, which can exhibit more immediate responses to program implementation. In contrast, anthropometric indicators like underweight, stunting, and wasting reflect long-term nutritional status[20] and may require more time to manifest changes in response to SURE-P implementation.

6. Discussions and mechanisms

6.1. General effect of SURE-P

As discussed in the introduction and Section 2, the SURE-P programme includes aspects of demand- and supply-side initiatives, which all have the potential to improve maternal wellbeing during pre- and post-birth periods. Fig. 5 generally describes these initiatives, including a cash transfer of approximately $30 to pregnant women registered at public primary healthcare facilities, incentivizing them to seek health services[21] (Oduenyi et al., 2019). In addition, there have been increases in the supply of trained health officers to strengthen the local capacity and staff composition for improved health service delivery (Dias et al., 2016), as well as infrastructural development and medical supplies to further strengthen service supply (Ezumah et al., 2022).

The implications of these demand- and supply-side initiatives on maternal wellbeing range from potential changes in household budget due to cash transfers (Armand et al., 2020; Ohrnberger et al., 2020) to maternal uptake of healthcare services. For example, evidence suggests that during the SURE-P rollout, there was a recorded increase in women (78% increase) who demanded healthcare services in the beneficiary facilities, including first neonatal immunizations and/or family planning advice (National Planning Commission, 2013). In addition, these initiatives resulted in increased interactions with skilled health workers in terms of community outreach and direct patient care. For instance, intensive advocacy visits and sensitization meetings were conducted with diverse stakeholders at the district and community/traditional levels to promote health information. Consequently, while there was a general increase in health service delivery by skilled health workers, some locations in Nigeria recorded over a 100% increase in various encounters with skilled health professionals, including births attended by skilled health personnel (National Planning Commission, 2013).

6.2. Mechanism

Despite the general effect of SURE-P on maternal wellbeing, what remains to be known is the reason for the improvement in child nutritional outcomes in SURE-P beneficiary locations, particularly in those districts with more than one SURE-P location. In this section, we look into this issue further by focussing on the labour market channel to show that health programs that improve the health of mothers can have an effect on the nutrition of their children by possibly increasing their earnings through better participation in the labour market. This is especially true when these programs remove geographic barriers that keep mothers from getting to health services.

Many of the questions about maternal labour market engagement were gotten from the DHS survey, including measurement related to employment status (a binary indicator if the respondent is currently working and the woman has worked in the past 12 months before the survey), outside options (a binary indicator if work is outside the household), seasonality of employment (1 if employment is all year and not seasonal), and remuneration status (i.e., whether cash is paid for work). These measures focus on a woman's employment status and the quality of her labour engagement. As a result, we can access how these measures respond to SURE-P implementation and the extensiveness of such implementation.

Table 5 presents the results of running regression (OLS) analysis with these outcome measures, each using a specific labour market indicator to highlight associations with SURE-P implementation. We do not test this regression for robustness, but instead, it only suggests associations between the indicators of SURE-P implementation and the indicators of labour engagement. As in Tables 2 and 3, we focus on the subset of women with children whose birth years correspond to periods pre- and post-SURE-P implementation (alongside variation by location based on SURE-P status) so that the labour market response corresponds to those potentially impacted by the programme.

Column 1 indicates a strong association between SURE-P implementation and increased maternal labour market engagement. Women residing in districts with one or two SURE-P beneficiary facilities are 7.8 and 6.5 percentage points more likely, respectively, to be working compared to those in districts without such facilities. Column 2 shows a similar positive association in the likelihood of women having worked in the past 12 months, a comparable and more specific measure capturing employment within the past year. The results indicate positive and significant effect for individuals in districts with one or two SURE-P beneficiary facilities, with stronger significant effects for women in two SURE-P beneficiary districts. The other columns in Table 5 indicate similar patterns, showing that women in districts with two beneficiary facilities record better quality of labour engagement.

Assessing the quality of women's employment is also important. Column 3 examines estimates for the indicator of women outside options, indicating a 7.3 percentage point increase in the likelihood of working outside the home for women in districts with two SURE-P beneficiary facilities. This effect is not observed for those in districts with one facility. Furthermore, analysing women's remuneration, Column 5 reveals a significant 53.4 percentage point increase in the likelihood of paid employment in cash for women in districts with two SURE-P facilities. These findings strongly suggest that improvements in maternal health are associated with higher labour market outcomes, including increased probability of employment and higher-quality jobs.

There are potential explanations why we find these labour market improvements specifically in districts with two SURE-P, our measure of extensive implementation of the health programme. One reason promoted in this study is that extensive implementation of the programme can help overcome geographic barriers to accessing healthcare for pregnant women, and thus, facilitating a quicker reintegration into the labor market. For example, a more extensive implementation can increase access to maternal healthcare and improved contact with health professionals, particularly in rural and remote areas where distance to health facilities remain a barrier for most pregnant women (Benyoussef and Christian, 1977; Bart et al., 2012; Druetz et al., 2017; Okeke, 2023).

We present suggestive evidence in Fig. 6a and b, which show that in locations with two SURE-P beneficiary facilities, women have more contact with health professionals during and after pregnancy. Since our primary data source (the DHS) does not have a direct measure of maternal contact with health professionals that is relevant to our study, we rely on suggestive indicators such as the number of antenatal visits and the probability of a family planning worker visiting the woman in the last 12 months. We plot the non-parametric estimates of the distribution of these measures by comparing locations with and without SURE-P beneficiary facilities, as well as varying numbers of SURE-P facilities within districts, over several years. This approach allows us to relate these indicators to each year and observe the evolution of changes over time.

Fig. 6a shows the probability of a woman having at least one antenatal visit over the year and across locations in our sample (i.e.,

[20] See Efobi (2024) and other studies that allude to the relevance of these indicators in accessing long-term nutritional status (see Van de Gaer, Vandenbossche, and Figueroa, 2014; Woldemichael et al., 2022).

[21] The transfers were given to those who registered at designated primary healthcare (PHC) facilities, received four ANC check-ups, gave birth at participating health facilities, or had their infants receive the first series of vaccinations at these facilities (Ezumah et al., 2022; Ogu et al., 2023).

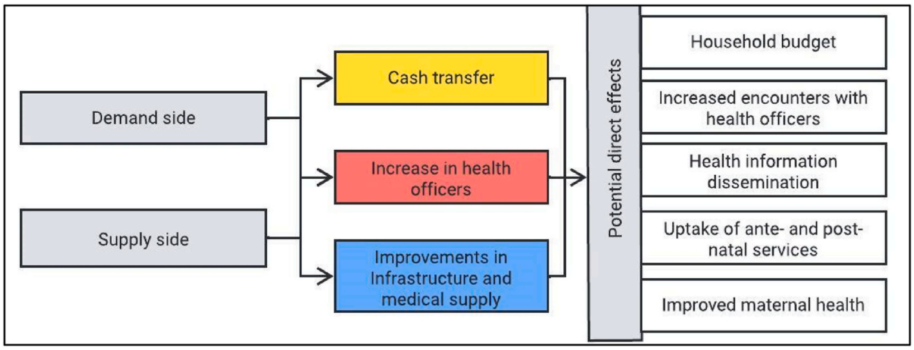

Fig. 5. Framework describing effect of SURE-P on maternal wellbeing.
Source: Authors' computation

Table 5
SURE-P implementation and maternal labor market outcomes.

	Probability of working	Probability of working in past 12 months	Outside options	seasonality of employment	Remuneration status
	[1]	[2]	[3]	[4]	[5]
SURE_P × Post	0.012 (0.020)	0.010 (0.021)	0.021 (0.018)	0.012 (0.024)	0.201 (0.199)
N	120,140	116,182	67,430	79,098	67,005
One SURE_P × Post	0.078** (0.033)	0.064* (0.033)	0.038 (0.028)	0.043 (0.036)	0.208 (0.293)
Two SURE-P × *Post*	0.065** (0.031)	0.077** (0.033)	0.073*** (0.025)	0.020 (0.038)	0.534** (0.254)
N	120,140	116,182	67,430	79,098	67,005

Note: The direct association between the indicators of SURE-P and the outcome variables are not reported for space, although available upon request. The measures for outside options, seasonality of employment, and remuneration status all apply for women who are currently working. Probability of working and working in the past 12 months are binary indicators if the woman reports in the affirmative to whether they are (or not) currently working and work in last 12 months before the survey was collected. Outside options is a binary indicator if the work of the woman is outside the household. Seasonality of employment is a binary indicator if the work of the woman is all year round and not seasonal or occasionally. Finally, remuneration status is a binary indicator if the work pays cash to the woman (reference is if the woman is not paid or paid in-kind only). Other notes are similar to those displayed in Tables 3 and 4 ***p < 0.01; **p < 0.05; *p < 0.1.

locations without any SURE-P, those with SURE-P, those with one SURE-P, and those with two SURE-P facilities). Our interest is in knowing the probability of this visit for women in these locations over the years. It shows that across all locations, there was a consistent increase in the probability of having one or more antenatal visits, but for women in locations with two SURE-P beneficiary facilities, there was a significant jump in this probability in periods after 2012. This jump in periods after 2012 is similar to Fig. 6B, which shows the probability of a family planning worker visiting the woman in the last 12 months. When comparing the increase in this probability in 2012 and beyond for women residing in locations with two SURE-P facilities, the increase seems to be obvious and higher compared to the increase in periods preceding 2012. In essence, the Figures suggest that women residing in locations with more clinics are those who report more contact with health workers, based on the indicators that we have used in this analysis.

The implication of these Figures is that beneficiary mothers that reside in locations with multiple SURE-P facilities are potentially more able to reintegrate faster into the labour market, seen mostly by the probability of working outside the home and earning cash, because they have more access and contact to health service delivery in their community. As a result, they are more able to participate in the labour market and earn better income (see Onarheim et al. (2016) for a systematic review of maternal access to health services and labor market participation). Therefore, if mothers labor market prospects are higher due to better access to health services, this in turn, could lead to higher household income (Molland, 2016; Heath and Tan, 2019) and better child nutritional outcomes through changes in maternal earnings, among others (Debela and Qaim, 2021; Hosen et al., 2023).

6.3. *Heterogeneity and consideration for future study*

Our analysis thus far has provided a general understanding of how the SURE-P program may improve child nutrition. However, it will not be completed without examining whether the programme's effectiveness varies based on specific characteristics of the SURE-P location – the population density of the districts. There are two obvious reasons why this analysis is important in the context of SURE-P distribution across locations. First, in terms of resource allocation, those districts with higher population densities may be those with more healthcare facilities and personnel (Raghupathi and Raghupathi, 2023). Consequently, the distribution of SURE-P demand- and supply-side resources might be more concentrated in these districts. Second, population density can influence accessibility to maternal healthcare services. Women in densely populated areas may have better access, unlike those in sparsely populated areas who might face challenges in reaching healthcare facilities (Doogan et al., 2018) and potentially leading to poorer maternal health outcomes.

This locational variation may determine the effect of SURE-P on our primary outcome variable. Hence, we explored this possibility by examining heterogeneous effects across districts with high and low population density. This is particularly relevant given our earlier observation in Table A3 of a positive correlation between expanded SURE-P implementation (districts with two SURE-P beneficiaries) and population density.

To categorize districts, we classified them into high and low population densities based on percentiles, following the approach of Arellano et al. (2024). Districts falling within the 25th percentile of the national population density distribution were considered low density, while those above the 75th percentile were considered high density. We excluded districts in the remaining percentiles from this analysis to better distinguish between the two groups.

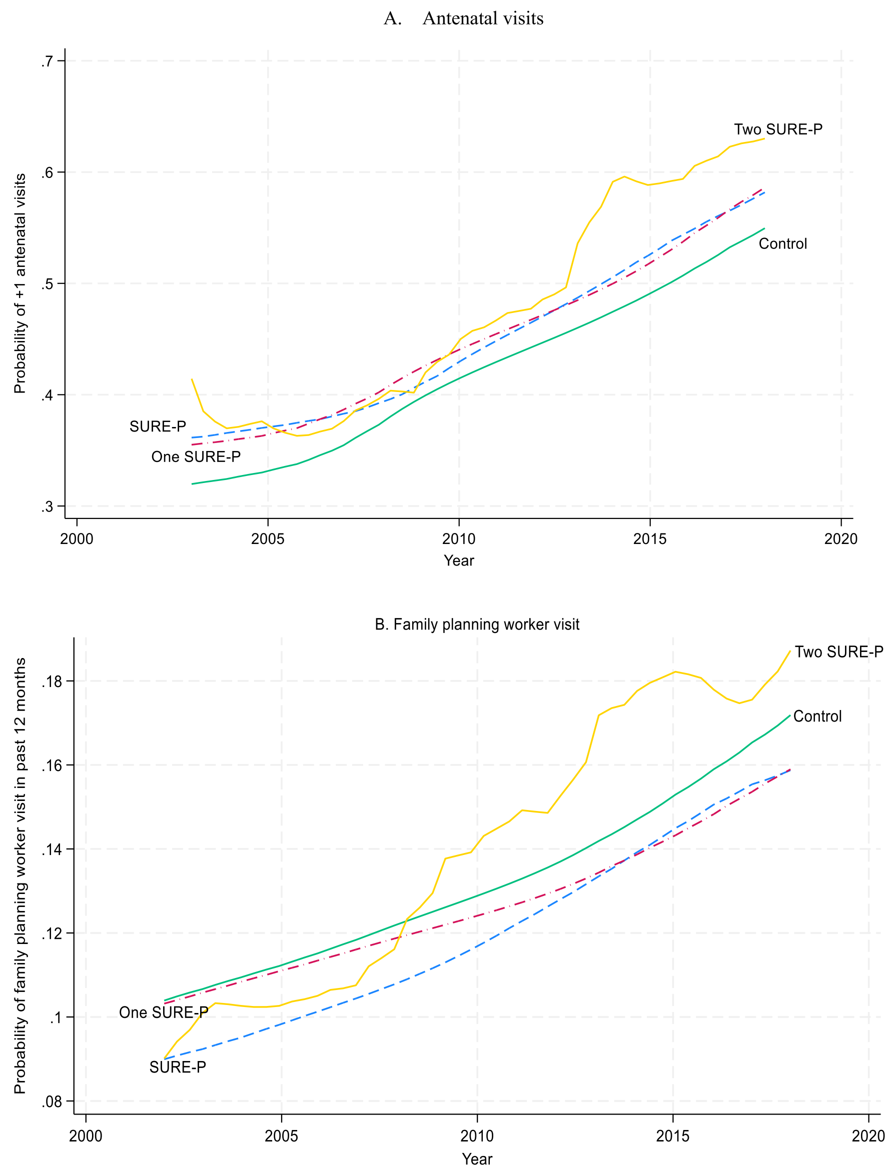

Fig. 6. Suggestive evidence of access to and contact with health professionals.
Note: SURE-P, One SURE-P, and Two SURE-P are as earlier defined. They are districts with any SURE-P, one SURE-P beneficiary facility, and two SURE-P facilities, respectively. Control are those districts without any SURE-P beneficiary facility. The Figures capture the probability of a woman having one or more than one antenatal visits (Fig. 6A), while Fig. 6B is the probability of the woman having a family planning worker visiting within the past 12 months. These measures are only suggestive indicators of a woman's access and contact with health professionals in the district they reside.

To assess potential heterogeneity, we re-estimated the main regression model (presented in the previous section) stratified by the population density category (≤25th vs.≥75th). The results of this analysis are presented in Fig. 7. Interestingly, our analysis revealed no significant differences in the programme's effect on child nutrition across districts. The absence of statistically significant effects for the individual dietary consumption indicators further supports these findings. While we earlier observed a positive correlation between SURE-P expansion and population density (see Table A3), our analysis here suggests that the programme's effect on child nutrition may be consistent across this range of densities. Selection bias is one possible explanation for the earlier correlation. Districts with higher population density may have been selected for expanded program implementation for reasons unrelated to the program's effectiveness.

Moreover, a high population density does not necessarily indicate a higher proportion of pregnant women, postpartum women, or newly delivered mothers. The composition of the population could vary significantly, and areas with higher overall density might still have a relatively low number of the specific beneficiaries targeted by the program. Therefore, it is plausible that other factors related to the programme design are driving the overall positive effect in locations with expanded SURE-P implementation, as shown in Table 3. These factors could include the number of medical personnel available, the effectiveness of medical information dissemination, and better access to quality healthcare in districts with two beneficiary SURE-P facilities.

It is also important to acknowledge that alternative explanations may exist for the observed improvements in dietary diversity in districts with multiple SURE-P beneficiary facilities. Improvements to transportation infrastructure during the programme period could be one such

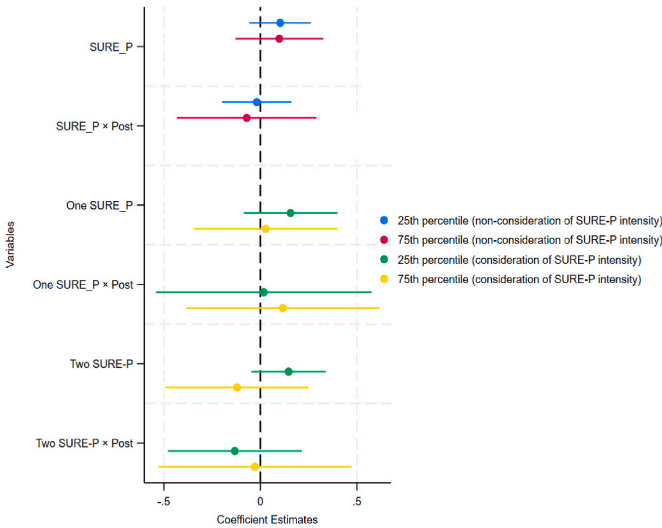

Fig. 7. Coefficient Plot of Effects by Population Density of the Location of the mother.
Note: The data for the population density was gotten from the DHS surveys that were used for the analysis. Specifically, we compute population density using the 2010 estimates that consists of high-resolution estimates of number of persons per square kilometer based on counts consistent with national censuses and population registers for 2010 (Mayala and Donohue, 2022). Estimates do not change when we use a different reference year and although not reported (available upon request), we also do not find heterogeneous effects for the other indicators of nutritional intake.

explanation, and changes in food prices due to the programme implementation could be another.[22] Improved transportation infrastructure from SURE-P resources, such as road construction or public transportation expansion (Atakpa, 2016), initiated by the government to alleviate transport challenges in Nigeria, might have been intensified in districts with multiple SURE-P,[23] leading to better access to diverse food markets and employment creation, among others. While we remain uncertain, these underlying conditions could potentially account for the observed improvements in child nutritional outcomes in our analysis, especially in districts with more SURE-P facilities. This likely mechanism, with the availability of data on transportation infrastructure improvements and food prices, could be a valuable consideration for future studies.

7. Conclusion

Recent literature has provided evidence suggesting that investing in maternal health service delivery, particularly by offering healthcare services for women during pregnancy and in the post-delivery period, can profoundly affect not only the mothers who receive care but also their infants. Our study contributes to this literature by exploring the effect of a health programme (SURE-P), and the expansive implementation of such programme, on child nutritional intake. Our data demonstrates that the children of mothers residing in districts with expanded program implementation (two facilities) exhibited significantly greater improvements in dietary diversity and child nutritional status (i.e., likelihood of consuming fruit & vegetables, green leafy vegetables, other fruits & vegetables, and animal source – food).

These findings offer valuable insights for policymakers and program implementers in similar contexts, even though the SURE-P program itself concluded in 2015. For example, expanding the reach of maternal health programs, potentially by establishing multiple service delivery points, can significantly improve child outcomes. This aligns with our observation that children in districts with two SURE-P facilities, indicating expanded access, showed greater dietary improvements. This is particularly relevant in underserved communities that might previously have been excluded due to structural barriers like distance and limited transport infrastructure. As a result, programme expansion could potentially result in equitable access to maternal health services and potentially reduce disparities in child outcomes.

Our data suggests a potential mechanism at play. Women exposed to the program, particularly those in locations with expanded SURE-P implementation, are more likely to report improved quality labor outcomes. Therefore, demonstrating that apart from maternal health, such targeted programmes with expanded implementation can have other downstream effects in empowering women's agency, including quicker reintegration into the labor market, which has implication on maternal earnings and overall child wellbeing.

CRediT authorship contribution statement

Uchenna Efobi: Writing – review & editing, Writing – original draft, Methodology, Formal analysis, Data curation. **Oluwabunmi Adejumo:** Writing – review & editing, Writing – original draft, Funding acquisition, Formal analysis. **Obianuju Nnadozie:** Writing – review & editing, Writing – original draft, Methodology, Funding acquisition. **Oluwasola Omoju:** Writing – review & editing, Writing – original draft, Funding acquisition. **Adeniyi Ekisola:** Writing – review & editing, Writing – original draft, Funding acquisition.

Disclosure statement

This research was not financially supported by any institution. The authors declare that they have no conflict of interest to disclose.

Ethical statement

Ethics approval not required.

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[22] Thanks to the reviewers for these suggestions.
[23] See the path dependency theory in public policy literature (e.g., Hiilamo and Glantz, 2015), suggesting that past public policy decisions influence future policy choices. In this case, the decision on locations that will benefit from the investment in transportation infrastructure may be those that have previously benefited from extensive SURE-P implementation.

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Kadengye, for their contributions.

APPENDIX

Table A1
Summary Statistics

	Mean	Std. Dev.	Obs.
Outcome variables:			
Dietary diversity (standardized) [a]	−2[b]08e-08	1.000	148,068
Dietary diversity (raw values) [b]	3.071	2.885	148,068
Fruit & vegetables	0.384	0.486	148,068
Vitamin A-rich fruit & vegetables	0.080	0.271	147,367
Green leafy vegetables	0.288	0.453	147,458
Other fruits & vegetables	0.147	0.355	147,426
Animal source-food	0.453	0.498	148,068
Primary covariates:			
Mother's: Age	31.595	6.872	148,068
Mother's: Primary school completion = 1	0.207	0.405	148,068
Spouse's: Age	42.360	10.200	142,786
Spouse's: Primary school completion = 1	0.192	0.394	143,962
Other wives in the household = 1	0.374	0.484	143,152
Rural dummy[a]=1	0.718	0.450	148,068
Household size	8.027	3.845	148,068
Number of under-5 children	2.457	1.247	148,068

[a] The[b]standardized measure of dietary diversity was used as the main outcome variable in the regression analysis to allow for easier comparison of effect magnitudes.

[b] The raw score was only included in the summary statistics and analyzed in a subsequent robustness check.

Table A2
Balance Check – Residents' Characteristics

	A. All women in the DHS sample			B. Women with infants		
	SURE-P district. (SURE-P)	District has at least one SURE-P facility. (One SURE-P)	District has 2 or more SURE-P facility. (Two SURE-P)	SURE-P district. (SURE-P)	District has at least one SURE-P facility. (One SURE-P)	District has 2 or more SURE-P facility. (Two SURE-P)
Mother's characteristics						
Age	0.000 (0.000)	−0.000 (0.000)	0.000 (0.000)	0.001 (0.000)	0.000 (0.000)	0.000 (0.000)
Primary school completion = 1	−0.013* (0.008)	−0.010* (0.005)	−0.015 (0.014)	0.002 (0.009)	−0.006 (0.006)	−0.015 (0.015)
Spouse's characteristics						
Age	−0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	−0.000 (0.000)	−0.000 (0.000)	0.000 (0.000)
Primary school completion = 1	0.006 (0.006)	0.003 (0.004)	−0.002 (0.004)	0.008 (0.007)	0.005 (0.005)	−0.002 (0.004)
Household's characteristics						
Other wives in the household = 1	0.004 (0.007)	−0.002 (0.004)	0.001 (0.004)	0.006 (0.008)	−0.000 (0.005)	0.006 (0.005)
Rural dummy = 1	0.010 (0.028)	0.001 (0.017)	0.006 (0.018)	0.013 (0.032)	0.011 (0.018)	0.011 (0.021)
Household size	−0.001 (0.001)	−0.000 (0.001)	−0.001 (0.001)	−0.002 (0.002)	−0.001 (0.001)	−0.002* (0.001)
Number of under-5 children	0.004* (0.002)	−0.001 (0.002)	0.006* (0.004)	0.005 (0.003)	0.001 (0.002)	0.005* (0.003)
R-squared	0.556	0.559	0.536	0.642	0.654	0.638
N	294,504	294,504	294,504	120,697	120,697	120,697

Note: We estimate different regression for all women in the sample and for women with infants. The dependent variables are presented at the top of each column, which is the probability of the district having SURE-P, having one SURE-P beneficiary facility, and having two SURE-P beneficiary facilities. Panel A are estimates for all women irrespective of whether they have infants (children below the age of 5), while Panel B are the estimates for only women with infants. The estimates show the association between the district status and the characteristics of women composed in such districts. *$p < 0.10$.

Table A3
Balance Check – Geographic Characteristics

	Total population (log)	Population density (log)	Total under-5 population (log)	Mean temperature	Malaria prevalence	Access to ITN	Cluster altitude	Travel time to community (log)
SURE-P	−0.100 (0.071)	−0.114* (0.061)	−0.095 (0.091)	−0.007 (0.066)	−0.002 (0.006)	0.003 (0.004)	0.160 (0.782)	0.105 (0.073)
R-squared	0.571	0.643	0.571	0.501	0.538	0.608	0.766	0.586
One SURE-P	0.081 (0.119)	0.139 (0.102)	0.110 (0.151)	−0.159 (0.124)	−0.008 (0.010)	0.009 (0.008)	0.369 (0.395)	−0.052 (0.125)
R-squared	0.571	0.643	0.570	0.502	0.539	0.609	0.767	0.585
Two SURE-P	0.174 (0.119)	0.228** (0.092)	0.185 (0.148)	0.093 (0.111)	−0.013 (0.011)	−0.010 (0.007)	0.081 (0.103)	−0.009 (0.124)
R-squared	0.571	0.644	0.571	0.501	0.539	0.609	0.765	0.585
N Districts	400	400	400	400	400	400	400	400

Note: The Table is presented differently, such that the variables at the top rows are the explanatory variables, while those at the left hand side, at the beginning of each row are the outcome variables. Hence, the coefficients are for different regression estimates, where the explanatory variables are displayed at the top of the column, while the outcome variables are the probability of the district having SURE-P, having one SURE-P beneficiary facility, and having two SURE-P beneficiary facilities. The cluster altitude is gotten from the DHS survey, represented in meters, but was transformed to its logarithm form for this analysis. The travel time to community is defined as the (log) average time (minutes) required to reach a settlement of 50,000 or more people from the area within the 2 km (urban) or 10 km (rural) buffer surrounding the DHS survey cluster location based on recent infrastructure data. Other measures are as defined. The estimates show the association between the district status and the different geographic variables. *p < 0.1; **p < 0.05.

Table A4
Robustness Checks

		Dietary diversity (raw score)	Dietary diversity (standardized) – excluding condiments
		[1]	[2]
Panel A: considered a non-standardized primary outcome variable and a measure of dietary diversity that excludes condiments.	*SURE_P*	0.061 (0.092)	0.023 (0.034)
	SURE_P × Post	0.078 (0.121)	0.029 (0.045)
	N	120,604	120,604
	One SURE_P	0.097 (0.170)	0.036 (0.063)
	One SURE_P × Post	0.004 (0.214)	0.002 (0.080)
	Two SURE-P	−0.267* (0.153)	−0.100* (0.057)
	Two SURE-P × Post	0.528*** (0.194)	0.197*** (0.072)
	N	120,604	120,604

		Dietary diversity (standardized)	Fruit & vegetables	Vitamin A-rich fruit & vegetables	Green leafy vegetables	Other fruits & vegetables	Animal source-food
		[1]	[2]	[3]	[4]	[5]	[6]
Panel B: Include district fixed effect: In these analyses, we incorporate the district fixed effect instead of the community fixed effect in all regressions.	*SURE_P × Post*	0.012 (0.039)	0.019 (0.020)	0.005 (0.009)	0.016 (0.017)	0.014 (0.013)	0.002 (0.019)
	N	120,604	120,604	119,926	120,023	119,988	120,604
	One SURE_P × Post	0.004 (0.068)	0.013 (0.034)	0.023 (0.016)	0.009 (0.030)	0.018 (0.023)	0.004 (0.031)
	Two SURE-P *× Post*	0.132** (0.064)	0.088*** (0.032)	0.001 (0.015)	0.069** (0.029)	0.044** (0.021)	0.060* (0.031)
	N	120,604	120,604	119.926	120,023	119,988	120,604
Panel C; Include intensity of ethnic fractionalization as a covariate. For this analysis we compute the proportion of individuals residing within the state who declare that they would choose their ethnicity over the national identity.	*SURE_P*	0.017 (0.032)	0.023 (0.015)	0.019** (0.009)	0.017 (0.014)	0.008 (0.010)	−0.015 (0.015)
	SURE_P × Post	0.026 (0.042)	0.028 (0.021)	0.002 (0.010)	0.026 (0.018)	0.014 (0.014)	0.006 (0.021)
	N	120,604	120,604	119,926	120,023	119,988	120,604
	One SURE_P	0.024 (0.060)	0.040 (0.025)	0.025 (0.016)	0.015 (0.025)	0.030 (0.019)	−0.033 (0.025)
	One SURE_P × Post	0.000 (0.074)	0.009 (0.036)	0.023 (0.018)	0.004 (0.032)	0.024 (0.023)	0.001 (0.035)
	Two SURE-P	−0.102* (0.053)	−0.019 (0.025)	−0.004 (0.013)	−0.042* (0.022)	−0.024 (0.015)	−0.045* (0.025)
	Two SURE-P *× Post*	0.174** (0.068)	0.090*** (0.033)	0.014 (0.015)	0.073** (0.030)	0.047** (0.022)	0.075** (0.033)
	N	120,604	120,604	119,926	120,023	119,988	120,604
Panel D: Including mothers household migration status, measured as a binary indicator if the mother/woman has always resided in the location she was surveyed (i.e., non-migrant).	*SURE_P*	0.022 (0.032)	0.025* (0.014)	0.021** (0.009)	0.018 (0.014)	0.010 (0.010)	−0.012 (0.014)
	SURE_P × Post	0.027 (0.042)	0.029 (0.021)	0.001 (0.010)	0.027 (0.018)	0.014 (0.014)	0.006 (0.021)
	N	120,604	120,604	119,926	120,023	119,988	120,604
	One SURE_P	0.034 (0.059)	0.045* (0.025)	0.030* (0.015)	0.018 (0.024)	0.033* (0.018)	−0.028 (0.025)

(*continued on next page*)

Table A4 (*continued*)

		Dietary diversity (standardized)	Fruit & vegetables	Vitamin A-rich fruit & vegetables	Green leafy vegetables	Other fruits & vegetables	Animal source-food
		[1]	[2]	[3]	[4]	[5]	[6]
	One SURE_P × Post	−0.002 (0.074)	−0.009 (0.036)	−0.024 (0.018)	−0.005 (0.032)	−0.024 (0.023)	0.000 (0.036)
	Two SURE-P	−0.092* (0.053)	−0.014 (0.024)	−0.000 (0.013)	−0.039* (0.022)	−0.020 (0.015)	−0.040 (0.024)
	Two SURE-P × *Post*	0.183*** (0.067)	0.095*** (0.033)	0.018 (0.015)	0.077*** (0.029)	0.051** (0.022)	0.079** (0.033)
	N	120,604	120,604	119,926	120,023	119,988	120,604
Panel E: We undertake a placebo test, wherein we designate the birth years 2016, 2017, and 2018 as the post-implementation period for the SURE-P program. This period corresponds to the conclusion of the SURE-P initiative. Utilizing these years as the SURE-P period enables us to evaluate the robustness of our initial estimates as presented in Tables 2 and 3	*SURE_P*	0.015 (0.028)	0.023* (0.012)	0.019** (0.008)	0.016 (0.012)	0.007 (0.009)	−0.015 (0.013)
	SURE_P × Post	−0.018 (0.025)	−0.005 (0.012)	−0.007 (0.006)	−0.000 (0.011)	−0.003 (0.008)	−0.011 (0.012)
	N	140,434	140,434	139,764	139,865	139,830	140,434
	One SURE_P	0.038 (0.051)	0.035* (0.021)	0.026* (0.014)	0.018 (0.020)	−0.003 (0.007)	0.025** (0.010)
	One SURE_P × Post	−0.062 (0.042)	−0.033 (0.021)	−0.016 (0.011)	−0.014 (0.019)	−0.008 (0.015)	−0.023 (0.021)
	Two SURE-P	−0.092** (0.045)	−0.007 (0.020)	−0.003 (0.011)	−0.035* (0.018)	−0.020 (0.012)	−0.046** (0.021)
	Two SURE-P × *Post*	0.057 (0.045)	0.035* (0.020)	0.002 (0.010)	0.030 (0.019)	0.023 (0.016)	0.013 (0.024)
	N	140,434	140,434	139,764	139,865	139,830	140,434

Note: Adjusted standard errors, shown in parentheses, account for clustering at the "community level." In all panels except Panel D, "Post" is a dummy variable set to one if the child was born in 2012 or later, coinciding with the implementation period of the SURE-P program. Each regression includes the following controls: the woman's age, the age of her current spouse, whether the woman completed primary school, whether the spouse completed primary school, whether there are other wives in the household, a rural dummy variable, household size, and the number of children under five in the household. Additionally, fixed effects incorporated into the regression are community-, mother-, survey year-, and the community-year of birth fixed effects (excluding Panel D). The district-specific trend is also accounted for in the regression. The analysis focuses on children born before 2015, except for Panel D. In Panel A, district fixed effects are included instead of community fixed effects, while other fixed effects and covariates remain consistent with Tables 2 and 3 Panel B measures ethnic fractionalization as the ratio of individuals in a state who identify solely or predominantly with their ethnicity over their Nigerian identity. In Panel D, the community-year of birth fixed effect is omitted due to its significant correlation with the interaction terms, resulting in a drop in the estimate from our results.

Data availability

The authors do not have permission to share data.

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