Childbirth and Healthcare: Developmental Evidence

Rufus Petrie
Professor Taber
Econometrics III
18 December, 2018

Abstract

In this paper, I estimate the impact that childbirth has on household healthcare spending in the context of a developing country. For my analysis, I use the KwaZulu-Natal Income Dynamics Study, a household survey from the KwaZulu-Natal region of South Africa. I model the impact that childbirth has on household healthcare spending by using fixed effects regressions and controlling for other economic factors. I find that childbirth has no statistically significant impact on household healthcare spending. This result holds regardless of model specification.

1 Introduction

As is the case with most economic studies, attempting to understand the dynamics of healthcare spending takes on a whole new complexion when studied in the context of development. A lack of access to financial institutions in these areas often forces individuals and groups of people to come up with their own solutions to standard financial problems. For example, people in developing countries often form insurance groups with their family and neighbors that aid each other when members suffers a negative economic shock [9]. People also rely on these informal financial groups for credit and other services, but these agreements often prove less effective than their formal counterparts because they have weaker disincentives against malfeasance [9]. Such unorthodox financial behavior makes studying healthcare in the developing world an especially challenging task.

Despite these difficulties, people have devoted a great amount of effort to studying healthcare in the context of development. In particular, researchers have focused on studying vaccination programs because of the large social benefit of such medicine. However, this focus on vaccines leaves an incomplete picture of how people consume medicine in the developing world because like any other goods, healthcare goods have varying demand elasticities. In particular, vaccines tend to have higher demand elasticities than other health goods because much of their benefit derives from runoff effects. Therefore, I examine how families change their healthcare spending in response to a presumably inelastic good, i.e. healthcare spending related to childbirth. In this paper, I find little evidence that childbirth alone induces any significant change in healthcare spending, regardless of model specification.

2 Literature Review

Although a fair amount of people have studied health spending in developing countries and the effect of childbirth on economics variables, not many people have studied them both in one context. In their 2004 Econometrica paper, Edward Miguel and Michael Kremer examine the impact of a de-worming program in Kenya. In this paper, they find that positive externalities alone (i.e. increased school enrollment due to decreased sickness) justify the costs of de-worming programs [6]. In their 2007 QJE paper, Miguel and Kremer also analyze the the impact that increased costs have on similar programs in Kenya. In this paper, they find that attempts to recoup costs of running de-worming programs decrease vaccine takeup by about 80%, regardless of whether participants received education about the benefits of vaccines [5]. Furthermore, healthcare markets often suffer in developing countries because skilled professionals often move to countries with stronger economies. For example, 37% of South African doctors have moved to more advantageous countries between the years 1996 and 2009 [7]. Combined with the already high costs of healthcare relating to childbirth, this makes formal care for childbirth very costly in developing contexts [10]. Other literature about healthcare and development tells a similar story to these papers, i.e. that increased spending on healthcare goods can have great positive impacts, but high prices lead to severe underconsumption of these goods.

From what we've seen so far, I don't believe that we should expect a particular result ex ante. Although people in developing countries may underuse vaccines, we don't necessarily know whether this behavior will translate to less elastic goods. However, it could also be the case that people in developing countries deal with childbirth and childcare through unorthodox means, just as they do with loans and insurance. Therefore, I expect that childbirth and healthcare spending will have a positive relationship, but I won't be surprised if this relationship has a low magnitude or level of significance.

3 Data

Table 3.1: Summary Statistics

Variable	Mean	Standard Deviation	Minimum	Maximum
Age	53.899	14.130	23.000	110.000
Male	0.646	0.478	0.000	1.000
African	0.847	0.360	0.000	1.000
Education	3.912	3.656	0.000	16.000
Household Size	6.512	3.963	1.000	34.000
Health	21.335	68.791	0.000	2083.333
Insurance	66.298	332.251	0.000	12000.000
Income	2123.103	4071.995	2.083	1.05e+05
Tobacco	27.834	61.469	0.000	1520.000
Alcohol	29.070	65.704	0.000	750.000
Traditional Medicine	60.789	237.362	0.000	4400.000
Births	0.294	0.719	0.000	8.000
N = 1990				

For my analysis, I use data from the Kwazulu-Natal Income Dynamics Study (KIDS henceforth) [4]. This study surveyed individuals and households in the KwaZulu-Natal region of South Africa in the years 1993 and 1998. Researchers gathered this data to help explain the persistent poverty experienced among the rural poor in South Africa following Apartheid. The surveys focused on factors relating to household characteristics, income and labor, health, and anthropometrics.

This dataset surveyed about 1,400 families in the year 1993 and followed up with about 1,100 in the year 1998. After reducing the dataset to households surveyed in both years and observations that didn't have any obviously miscoded values, we have observations on 995 families across two years. Because we're studying the economic impact of childbirth on healthcare, I generated a variable that counted how many surviving children each family had in the time period between surveys. For my regressions, I regress this variable and a group of covariates on household healthcare spending. In particular, I include variables describing the age, gender, and education of the household head to control for variations in healthcare spending due to these factors. With everything else held equal, I would expect older, educated women to spend more on healthcare on average. Furthermore, I include variables for household size, income, insurance spending, tobacco spending, alcohol spending, and spending on traditional medicine to control for other preferences that may affect healthcare spending. All of the spending variables are monthly amounts and are measured in the South African rand.

From Table 3.1, we can start to get a sense of the typical household in the KwaZulu-Natal region. The average household head is 53.9 years old, male, and has fewer than four years of education. 84.7% of the households are African, and 15.3% of the households are Indian. The average household has somewhere between 6 and 7 members. The average household has an income of about 2,100 rand per month, and they spend about 21 rand on healthcare. For comparison, the average household spends more on alcohol and cigarettes each month.

4 Econometric Methods

To model the impact of childbirth on healthcare spending, I use fixed effects regressions. This type of regression derives its coefficient estimates from variations in behavior within households. This helps to account for individual (household) heterogeneity because it effectively adds an indicator variable for each household into the regression. This will control for all invariant household characteristics that have a constant impact of healthcare spending. For instance, if a household simply distrusts medicine and spends a fixed amount less on healthcare each year because of this distrust, a fixed effects regression will control for this type of variation. In addition to the household level variables included in the regression, this should help to explain variations in healthcare spending.

Additionally, I made some modifications to the data to help identify changes in healthcare due to childbirth. Firstly, I split the household size variable into three groups pertaining to members aged zero to one, members aged two to five, and members aged six and older. Ceteris paribus, we would expect families with more members to spend more on healthcare, so including these variables helps to isolate changes in healthcare spending relating to childbirth and ignore changes relating to an increase in the amount of young family members. Furthermore, we should note that personal savings often finance an individual's spending on insurance and healthcare, and the marginal propensity to save often changes with respect to an individual's income. Because of this, I model the natural logarithm of healthcare spending to account for this type of nonlinear relationship. Therefore, I estimate the following regression equation:

$$H_{i,t} = \alpha + X'_{i,t}\beta + Treat_{i,t}\gamma + \delta_i + \epsilon_{i,t} \tag{4.1}$$

In Equation 4.1, $H_{i,t}$ refers to the natural logarithm of health spending of household i at time t. α refers to the intercept term that is the same for all households and across all time periods. $X'_{i,t}$ refers to a vector of covariates for household i at time t. These covariates include the age, gender, and education of the household head[1]. The covariates also include the age counts of household members, income, and spending on insurance, tobacco, alcohol, and traditional medicine. β refers to the vector of regression coefficients associated with all of these covariate terms. $Treat_{i,t}$ refers to a dummy variable that equals if household i had a child between time t and $t-1$ (this equals 0 for all households in 1993). γ refers to the regression coefficient associated $Treat_{i,t}$ variable. δ_i refers to the fixed effect term for household i. $\epsilon_{i,t}$ refers to the residual term for household i at time t.

In addition to Equation 4.1, I also estimate a model with different treatment effects describing the number of children that each household had. The equation then becomes:

$$H_{i,t} = \alpha + X'_{i,t}\beta + Treat_{i,t}\Gamma + \delta_i + \epsilon_{i,t} \tag{4.2}$$

The variables and coefficients in Equation 4.2 mostly have the same meaning as their counterparts in Equation 4.1 except for $Treat_{i,t}$ and Γ, which denote vectors instead of scalars. In particular, $Treat_{i,t}$ contains dummy variables describing whether families had one child, two children, or three or more children[2]. At the cost of reduced precision of each coefficient estimate, this allows us to judge whether different numbers of births had different impacts on healthcare spending.

For these types of model to work, we need to assume the exogeneity of the childbirth variable(s). In other words, model covariates and fixed effects must control for any characteristic differences between households that had children and households that

[1] Fixed effects don't completely control for these because of turnover in household heads.

[2] This is as granular as I could make the treatment without having very few observations per coefficient.

didn't have any children. Furthermore, these must also control for any characteristic differences between households that chose to have different amounts of children between the survey rounds. In particular, we require that $E[\epsilon_{i,t}|X'_{i,t}, Treat_{i,t}] = 0$. This ensures that the counterfactuals in the regression mimic the behavior of families that opted to have children but did not end up with any. This assumption seems feasible enough because the household fixed effects in the regressions control for any constant differences that may relate to different values for the childbirth variable(s). Furthermore, some of the household level variables like income and household size will likely account for differences between families that affect both healthcare spending and the likelihood to have children. Finally, because of the general lack of education and large family sizes in the sample, we can safely assume that our observations did not engage in much family planning. This indicates a lower likelihood that the childbirth variable has any significant association with factors external to the model that could also affect healthcare spending. Bearing this in mind, we can safely assume that exogeneity of the childbirth(s) variables.

Once we assume the exogeneity of our covariates and the time invariance of any potentially endogeneous variables, we can then assert that the parameter γ uniquely identifies the difference in the natural logarithm of healthcare spending between families who had children and families who didn't have any. Furthermore, let the parameter Γ_j refer to the entry of Γ associated with having j children. Then, we can assert that the parameter Γ_j uniquely identifies the difference in the natural logarithm of healthcare spending between families who had j children and families who didn't have any children.

Finally, I estimate clustered standard errors for the regressions. Many people in this sample live in rural areas that likely rely on agriculture to maintain their living standards, and homogeneous shocks could affect these communities. For instance, natural disasters such as floods, forest fires, etc. that negatively impact agriculture would likely have a similar negative economic effect on most people living in the area. Therefore, we have strong evidence to believe that observations in this sample have positively correlated residuals, and this would invalidate the standard *i.i.d.* residual assumption. However, we can relax this assumption by using clustered standard errors, which will allow us to make better standard error estimates and avoid overstating statistical significance [2]. For my clusters, I use two-way clusters that include household ID and geographic areas (these roughly correspond to census tracts).

5 Results

To get a better sense of how model specification affects the relevant coefficients, I estimate four regressions for both the single and multiple treatment effects in Tables 5.1 and 5.2. For regression (1), I run a simple linear regression that only includes the natural logarithm of healthcare spending and the treatment dummies. Then, regression (2) adds an array of household covariates, regression (3) adds household fixed effects, and regression (4) adds clustered standard errors.

Table 5.1 contains the results from the regressions modeling the single treatment effect. As we can see, these regressions provide little evidence that childbirth causes any change in the level of household healthcare spending. In regression (1), the simple regression, the treatment has a positive coefficient and statistical significance at a high level, but this significance fails to survive any of the robustness checks. In particular,

Table 5.1: Impact of Any Births on Health Spending

	(1) lnHealth	(2) lnHealth	(3) lnHealth	(4) lnHealth
Any Births	0.268***	-0.062	-0.028	-0.028
	(0.081)	(0.086)	(0.123)	(0.129)
Age		0.007**	-0.001	-0.001
		(0.003)	(0.007)	(0.007)
Male		0.051	0.019	0.019
		(0.066)	(0.172)	(0.180)
Education		0.012	-0.015	-0.015
		(0.011)	(0.025)	(0.023)
Residents Aged 0-1		0.039	0.063	0.063
		(0.065)	(0.092)	(0.086)
Residents Aged 2-5		0.109**	0.155**	0.155**
		(0.036)	(0.057)	(0.051)
Residents Aged 6+		0.016	0.030	0.030
		(0.011)	(0.020)	(0.021)
Insurance		-0.000	-0.000*	-0.000*
		(0.000)	(0.000)	(0.000)
lnIncome		0.158***	0.128*	0.128*
		(0.033)	(0.052)	(0.063)
Tobacco/Alcohol		0.001*	0.001	0.001
		(0.000)	(0.000)	(0.000)
Traditional Medicine		0.002***	0.002***	0.002***
		(0.000)	(0.000)	(0.000)
Constant	1.940***	0.121	0.764	0.766
	(0.038)	(0.233)	(0.503)	(0.653)
Fixed Effects	No	No	Yes	Yes
Clustered	No	No	No	Yes
Observations	1990	1983	1983	1976

Standard errors in parentheses: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 5.2: Impacts of Number of Births on Health Spending

	(1) lnHealth	(2) lnHealth	(3) lnHealth	(4) lnHealth
One Birth	0.251**	0.007	-0.022	-0.022
	(0.097)	(0.093)	(0.130)	(0.140)
Two Births	0.188	-0.322*	-0.045	-0.045
	(0.156)	(0.159)	(0.234)	(0.218)
Three+ Births	0.551*	-0.140	-0.107	-0.107
	(0.230)	(0.240)	(0.345)	(0.291)
Age		0.007**	-0.001	-0.001
		(0.003)	(0.007)	(0.007)
Male		0.050	0.020	0.020
		(0.066)	(0.172)	(0.180)
Education		0.013	-0.014	-0.014
		(0.011)	(0.025)	(0.024)
Residents Aged 0-1		0.067	0.069	0.069
		(0.067)	(0.096)	(0.088)
Residents Aged 2-5		0.115**	0.159**	0.159**
		(0.037)	(0.060)	(0.046)
Residents Aged 6+		0.018	0.032	0.032
		(0.011)	(0.021)	(0.021)
Insurance		-0.000	-0.000*	-0.000*
		(0.000)	(0.000)	(0.000)
lnIncome		0.160***	0.126*	0.126
		(0.033)	(0.052)	(0.064)
Tobacco/Alcohol		0.001*	0.001	0.001
		(0.000)	(0.000)	(0.000)
Traditional Medicine		0.002***	0.002***	0.002***
		(0.000)	(0.000)	(0.000)
Constant	1.940***	0.083	0.755	0.758
	(0.038)	(0.233)	(0.508)	(0.674)
Fixed Effects	No	No	Yes	Yes
Clustered	No	No	No	Yes
Observations	1990	1983	1983	1976

Standard errors in parentheses: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

once we add covariates, household fixed effects, and clustered standard errors to the regressions, as we do in regression (2), (3), and (4), we can not reject the null hypothesis that childbirth has no impact on healthcare spending at the 95% level of significance. In regression (3) and (4), we see that the treatment effect still has a positive, so on average families who had children did spend more on healthcare, but the lack of statistical significance prevents us from drawing any inference from this number.

Table 5.2 contains the results from the regressions modeling multiple treatment effects. As is the case with the single treatment regressions, these regressions fail to provide any evidence that childbirth causes any significant change in household healthcare spending levels. In regression (1), we see that the coefficients for having one birth and having three births have positive and statistically significant signs. However, once we add the other covariates, fixed effects, and clustered standard errors, we can not reject the null hypothesis that childbirth led to no change in healthcare spending, regardless of the number of children a family had. Once again, all of these coefficients have positive signs, but we can not draw any inference from them because they have such large standard errors.

Although these regressions do not provide any significant results for our variables of interest, we can still see some interesting relationships in the other covariates. In regression (4) in Tables 5.1 and 5.2, we could not reject the null hypothesis that the age, sex, and education of the household head did not have any impact on healthcare spending. We should take this with a grain of salt because these factors had such little variation, but this still runs contrary to my intuition that older, educated females would spend more on healthcare. Furthermore, the age bin describing residents aged two to five maintained statistical significance at the $< 1\%$ level, whereas the other bins did not. This might make sense if the families surveyed lack the resources to deal with illnesses affecting very young children, but changing the bin cutoffs may affect this result. Finally, household spending on traditional medicine maintained significance at the 0.1% level through all of the regressions, which made it the most significant out of all the control variables. Also, contrary to what we might expect, spending on traditional medicine also had a positive association with spending on healthcare. Because of this extremely strong association, examining traditional medicine may provide interesting results in future research.

6 Discussion

Overall, this analysis provides little evidence that childbirth induces families in the KwaZulu-Natal region of South Africa change their level of healthcare spending. Although this may seem strange at first, a few possible explanations can account for this lack of responsiveness. Firstly, the general lack of education among the populace may explain the lack of an effect. From Table 3.1, we saw that the household heads in the sample attained 3.91 years of education on average. This could affect decisions about healthcare spending in a couple different ways. Firstly, a general lack of knowledge about healthcare may mean that people simply don't know about potential treatments and precautions. Additionally, a lack of education signifies a lack of investment of human capital, which could explain reluctance to allocate other savings towards healthcare spending. For example, somebody with an MBA might feel comfortably taking out a loan on their house to pay for medical bills because a decrease in home equity wouldn't necessarily impact their future earnings. However, in agrarian societies, individuals likely rely more on accumulated physical capital to generate their income. This means that digging into their savings to pay for expensive medical bills would likely have a larger impact on their future income, which would deter them from taking such actions.

Larger households could also help to explain why childbirth didn't have any significant impact on healthcare spending. From Table 3.1, we see that the average household in this sample has 6.5 members on average. Combined with the fact that the average household head is 53 years old on average, we can safely assume that multiple generations of the same family often live together. Previous research has found that over a quarter of South African children live with pension recipients and that the children receive significant care from these household members [3]. All of this could imply that households substitute care from elderly members of their household for formal healthcare in the years following childbirth. Although I had no way of testing this theory, future researchers could also incorporate the amount of generations or branches living in a single household into this type of analysis.

We should also consider whether we should use the number of children that survived to count the number of births per family. This could affect the accuracy of our estimates if the families with children who died at a young age have different attitudes towards healthcare on average. For instance, having children die prematurely could indicate that these families to not consume much healthcare. This would bias our results downward because these families didn't spend much on healthcare following a pregnancy, but these families wouldn't appear in our treatment group because they didn't have any surviving children. On the other hand, families who had a child die may have spent a lot of money on healthcare for the child, and omitting them from the group of families who had children would actually understate the impact that childbirth has on healthcare spending.

A few features of the KIDS study probably also hurt the validity of this analysis. Firstly, I could not find any sample weights to adjust my coefficient estimates. Surveys like these typically oversample from easy-to-reach areas and use weighting later on to control for any potential bias. If this is the case, then the data likely underrepresents people living in extreme poverty, and this would lead to a positive bias in my results. Furthermore, no spending variables in this dataset adjust for inflation in South Africa, and I could not find any deflators to adjust the prices. Therefore, my coefficient estimates denote changes in nominal variables.

In the future, researchers could also investigate the the role that traditional medicine plays in household decisions. According to the World Health Organization, traditional medicine in this context likely refers to using substances from plants, animals, or minerals for health purposes; traditional medicine also sometimes includes social or religious rituals [8]. Unlike most other variables in my regressions, traditional medicine maintained statistical significance at the $< 0.1\%$ level throughout the robustness checks. Furthermore, healthcare spending and spending on traditional medicine have a positive correlation, which suggests that the two goods are complements. Therefore, understanding the healthcare decisions in developing South Africa probably requires a more detailed analysis of attitudes towards traditional medicine.

Future research could also be improved by attempting to model different heterogeneous treatment effects. Although I found no evidence that different numbers of births had any impact on healthcare spending, researchers could also test whether healthcare spending behaves the same way for male and female births. In other developing, agrarian societies, families tend to devote more resources to male children when they expect that those children will either work for them or care for them in their old age. This often leads to stunting in children, particularly girls, because of the physical demands of labor and an allocation of food that favors male family members [1]. Therefore, it would be interesting to see if this preference towards male children also persists in healthcare spending.

Finally, future research could improve upon these findings by modeling healthcare spending with more time periods and a higher frequency. In particular, modeling an event study would give valuable information about the dynamics of childbirth and healthcare spending. Firstly, access to data with a higher frequency would allow researchers to get a better idea of how childbirths affect healthcare spending close to the actual birth. In this data, we can not tell whether families who had children had them the day after the first survey round or the day before the second survey round, and timings like these would likely affect their healthcare spending. Furthermore, this would also allow us to get a better idea of how multiple pregnancies affect healthcare spending as we could disentangle the impact of each pregnancy. Finally, better data would allow us to see whether these families had any trends in healthcare spending prior to the pregnancies or made adjustments in anticipation of childbirth.

7 Conclusion

In my analysis, I find little evidence that childbirth induces any change in healthcare spending in the KwaZulu-Natal region of South Africa. After controlling for a variety of household factors and estimating cluster robust standard errors, I could not find any statistically significant relationship between childbirth and healthcare spending. Childbirth may have a positive relationship with healthcare spending insofar as it increases the number of young members in a household, but nothing from this analysis tells us that families change their behavior in response to childbirth alone. Researchers can improve upon the findings of this paper in the future by finding data with the same level of detail but with more time periods and a higher frequency. Additionally, any research performed in South Africa would do well to try understanding the role that traditional medicine plays in determining household healthcare decisions.

References

[1] Blessing J. Akombi, Kingsley E. Agho, Dafna Merom, Andre M. Renzaho, and John J. Hall. Child Malnutrition in Sub-Saharan Africa: A Meta-analysis of Demographic and Health Surveys (2006-2016). *PLOS ONE*, 12(5):1–11, 05 2017.

[2] Christopher F Baum, Austin Nichols, Mark E Schaffer, et al. Evaluating one-way and two-way cluster-robust covariance matrix estimates. In *presentation made for the 16th UK Stata User Group Meeting*, 2010.

[3] Esther Duflo. Grandmothers and granddaughters: Old age pension and intra-household allocation in south africa. Working Paper 8061, National Bureau of Economic Research, December 2000.

[4] International Food Policy Research Institute (IFPRI). *South Africa, KwaZulu-Natal Income Dynamics Study (KIDS), 1993-1998.* Harvard Dataverse, 2000.

[5] Michael Kremer and Edward Miguel. The illusion of sustainability*. *The Quarterly Journal of Economics*, 122(3):1007–1065, 2007.

[6] Edward Miguel and Michael Kremer. Worms: identifying impacts on education and health in the presence of treatment externalities. *Econometrica*, 72(1):159–217, 2004.

[7] Saraladevi Naicker, Jacob Plange-Rhule, Roger C Tutt, and John B Eastwood. Shortage of healthcare workers in developing countries–africa. *Ethnicity & disease*, 19(1):60, 2009.

[8] World Health Organization et al. *The promotion and development of traditional medicine: report of a WHO meeting [held in Geneva from 28 November to 2 December 1977].* Geneva: World Health Organization, 1978.

[9] Debraj Ray. *Development economics.* Springer, 2008.

[10] Xiao Xu, Aileen Gariepy, Lisbet S Lundsberg, Sangini S Sheth, Christian M Pettker, Harlan M Krumholz, and Jessica L Illuzzi. Wide variation found in hospital facility costs for maternity stays involving low-risk childbirth. *Health Affairs*, 34(7):1212–1219, 2015.