Effects of Banning Informal Attendance on Newborn Health in Malawi

Introduction

The government of Malawi, one of the African countries that has the highest maternal mortality ratio (currently 439 maternal deaths per 100,000 live births), introduced a controversial ban on informal birth attendants in 2007 in order to alter local household health. Godlonton and Okeke, authors of the original paper, applied a difference-in-difference strategy, which found a 15% decline in the use of traditional attendants, and no statistically significant evidence showing that the newborn mortality rate had been reduced by the new controversial ban.

By doubting whether the ban has no positive effect on newborn health, we extended the original paper from two aspects. First, we performed a robustness check and found that the newborn death rate, the original response variable, does not strictly follow the parallel assumption. Thus, in order to estimate the causal effect of the ban law more accurately, we chose newborn weight instead of mortality rate as an alternative indicator of health. Although the parallel assumption is valid under the new measurement, we found a weak causal relationship between the restrictions on informal providers and newborn weight.

Recall the original paper where the authors were using the data from the 2010 Malawi Demographic and Health Survey. Although the large shift from the informal to formal sector demonstrates some effects of the ban policy, it does not transfer into reductions in newborn mortality. Due to the lack of significant improvements in newborn outcomes, we transfer to our second extension. We conducted an OLS regression examining whether there is a difference between formal and informal in the health of newborns in 2010 and 2015-16. As a result, the probability of a baby born with a healthy weight increased significantly according to the 2015-16 data. Considering the increase in medical expenditure(about 77% from 2010 to 2016), the quality of the formal providers might also increase in the long run, which suggests that when adequate medical quality is ensured, the effectiveness of the policy on health outcomes will gradually be revealed.

Data

The 2010 Malawi Demographic and Health Survey was used for analysis, which was implemented by the National Statistical Office (NSO) from June to November 2010, with a nationwide sample of over 27,000 households. Eligible women aged from 15 to 49 and men aged from 15 to 54 were interviewed individually by taking health questionnaires. However, that survey data is not comprehensive to this article's investigation question-- whether the ban on informal health providers improves health outcomes, since the original article only talked about the effects of the ban law on the newborn based on the baby mortality, but no data indicates maternal mortality change. Another potential problem of the data is on the survey design. The 2010 MDHS sample includes 849 clusters: 158 in urban areas and 691 in rural areas. However, the 849 clusters were not allocated by the proportion of their population share, whereas the urban areas were oversampled since there were too few clusters to represent them, which might overestimate Malawi's health situation.

The 2015-2016 Malawi Demographic and Health Survey was also implemented by the NSO from October 2015 to February 2016 from 28 districts in the country. 26,000 randomly sampled households were interviewed by questionnaire with around 21,000 households in rural areas and the other 5,000 households in the urban area, which might also indicate an oversample of the urban household and overestimate the country’s health situation.

Method

In this article, the author investigated the causal effect of the ban law on outcomes by using the difference-in-difference (DD) strategy. The author exploits variation across time and space in the “intensity of exposure” to the ban to design the 'treatment group' and 'control group'. The treatment group is “High-exposure areas” that correspond to areas with informal attendant use exceeding the 75th percentile. Otherwise, the village will be defined as a low-exposure area.

However, we examined the parallel trend assumption of the probability of a newborn death (Susan, 2015), and we found that the trends in both areas were not strictly parallel prior to the introduction of the ban which was in 2007. Therefore, we try to modify the response variable which could be more reasonable to apply to the DD model. Since we want to further investigate the causal effect of this ban law on newborn health based on measurements except for the mortality rate. The newborn weight can be considered as a health measurement according to the WHO child growth standard. Therefore, we used the proportion of babies with healthy weight and keep the independent variables the same as the original paper:

$$\boldsymbol{Y\_icdtW = \alpha_1 + \alpha_2 Post_t + \delta HighExposure_c + \gamma HighExposure_c * Post_t + X_{ict}\beta + \eta_d + \tau_t + \epsilon_{icdt}}$$

Y_icdtW indicates the probability that the weight of child i in cluster c in district d born in time t is in WHO newborn standard weight range. *Post_t* is an indicator variable equal to 1 if a birth took place after the ban was introduced (Post = 1 if the child was born after December 2007). *HighExposure_c* indicates a DHS cluster with a historical prevalence rate ≥ 75th percentile. γ identifies the causal effect of the ban on newborn health. *X_ict* is a vector of individual, household and village characteristics. *η_d* is district fixed effects. *τ_t* is year × birth month dummies to capture time trends and *ϵ_icdt* is the error term.

Before the application of DD, we tested the parallel trend assumption of low-exposure and high-exposure-area in the proportion of infants with healthy birth weight. Based on the result in Figure1, although treatment and comparison groups have different levels of the outcome prior to the start of treatment in 2007, their trends in pre-treatment outcomes are roughly the same. Even the trends during the beginning of 2005 were not strictly parallel to each other, but this parallel trend assumption is better than the original paper. Hence, the DD strategy can be applied with the high-exposure area as the treatment group and low-exposure area as the control group, and estimate whether the increasing exposure of this ban law will lead to significant improvements in newborn healthy weight outcomes.

Also, we used OLS to test the difference in neonatal health levels between formal and informal birth attendants to explore specific reasons for the ineffectiveness of the policy. Using the OLS method, we can estimate the average relationship between the choice of informal or formal and the newborn health level by minimizing the sum of the squared error. To prevent the omitted variable bias, we controlled gender, education level, religion, and other possible variables that might influence the outcome in our model.

The estimating equation can be written as the following:

$$Y_{icdt} = \alpha_0 + \alpha_1 * Formal_{icdt} + \beta * X_{icdt} + \varepsilon_{icdt}$$

Y_{icdt} indicate the probability that the newborn i in cluster c district d born in time t is healthy. $Formal_{icdt}$ is the dummy variable that indicates whether the newborn i in cluster c district d born in time t use a formal attendant. X_{icdt} indicate all the control variables including gender, religion, education level, wealth level, district, cluster, born time and etc. for the newborn i cluster c in district d born in time t.

Results

Table 1 column 5 shows the DD model that by controlling all the variables except cluster fixed effect, babies in the high-exposure area will have a 1.44% higher probability of having healthy weights compared with low-exposure areas. However, the result is not statistically significant since the p-value is larger than 0.05. This result indicates that increasing the exposure of the ban law does not lead to significant improvements in newborn healthy weight level outcomes. Further investigation is needed on how the informal to formal sector transformation affects newborn health.

We use four standards to estimate the effect of the formal attendant on the newborn health, whether the baby is born alive, whether the baby is born with a healthy weight, and the mortality of the newborn in one week and one month. In 2010, we found that given all else constant, using a formal birth attendant is correlated with a 2.11% increase in the probability that the baby is born alive on average, a 2.76% increase in born with a healthy weight on average, a 0.467% decrease in baby dies within one week, and a 1.07% decrease in baby dies within one month. The results are neither statistically nor economically significant at the 5% significant level. Hence, we conclude that the difference in newborn health between formal and informal is very limited in 2010.

Considering the results from 2015-2016, we can see that using a formal birth attendant is correlated with a 0.635% decrease in the probability that the baby is born alive on average, this estimation is neither statistically nor economically significant. Using a formal birth attendant is correlated with a 7.78% increase in the probability that the baby is born with a healthy weight on average, which has a p-value less than 0.05 indicating statistical significance. The effect of formal birth attendant on mortality, both in one week and one month is less than 0.1% which is not economically and statistically significant. In conclusion, in 2015-2016, we find that the difference of the probability of being born with a healthy weight between informal and formal became significant, and the difference remains not significant using other criteria.

Discussion and Limitation

The MDHS was conducted in 2010, while the law was implemented in 2007, the participants were asked to provide information about years ago, and the values in the dataset might not be accurate as people might not remember some of the answers. Additionally, informal sectors might not provide valid information as well. As a result, there would exist recall bias, and the result might not be valid. Moreover, the dataset lacks information on variables that might correlate with a baby's health and the control variables. For example, maternal health information was not included, which would affect an infant's health and the control variables such as the mother's age. Consequently, we would face omitted variable bias issues, and the results may be over or under-estimated.

Difference-in-Difference (DD) models were conducted since it shows the effect of implementing a banning policy on babies' health, and such a method delivers a causal estimate. Overall, it fits the research question. However, there are some limitations. The control and treatment groups chosen are not optimal. Instead of grouping households not exposed to the ban of using informal attendance as the control group, we choose districts with low exposure as the control group since no data can be found in areas similar to Malawi in all aspects but the policy. There might be a spill-over effect as the households in the control group are also exposed to the policy, and their behavior might be affected. Consequently, our estimation of the effects might not be accurate, and the DD model may not explain much of the variance of the healthy weight dummies. The parallel trend assumption is required when conducting a DD model. According to Figure 1, we can see that from 2005 to 2006, the parallel trend assumption is violated since the increase in the probability of infants with a healthy weight is slightly higher in the treatment group. The referred paper faces the same problem as the trends for newborn deaths within a week and within a month are not parallel between the two groups. In addition, we might encounter external validity. Malawi is unique as the quality of healthcare sectors could even be lower compared to other third-world countries. Thus, the results might not generalize.

Even though the DD model shows the causal effect of the policy on a baby's health, it has various limitations, and it has been 11 years since the survey was done. Fortunately, we have found an updated survey done in 2015. We conducted OLS models to find the correlation between the use of formal attendance and the probability a baby has a healthy birth weight. DD model is not an option since the data were collected on babies born in 2010 and later, which means they were all exposed to the policy. Based on the original paper, the policy had a significant positive effect on the use of formal attendance, while the impact on health was not significant. The OLS models showed the impact of the policy on a baby's health indirectly as households are required to choose high-quality formal clinics, and the use of formal attendance has increased the baby's probability of being born with a healthy weight. However, this method has limitations as well. Reverse causality is one issue, as there might be a chance that mothers in wealthier families tend to have healthier children and are more likely to choose formal attendance. Furthermore, omitted variable bias, measurement errors and the external validity could cause problems.

Overall, the policy is more of an empty talk on saving babies' lives. Without a well-established healthcare system, implementing the law would not make fundamental changes as the quality in healthcare clinics are low even in formal sectors. Besides, banning the use of informal birth attendance might even increase the economic burdens of the citizens and worsen households' welfare. Therefore, Malawi should invest more in its healthcare system first so that people can access higher quality services by approaching formal attendance, and lives may be saved by implementing the law.

Conclusion

Based on our research, we believe that this policy has been implemented too early for Malawi. This policy transferred mothers who might use informal delivery methods to the formal sector. However, we found no significant difference between using the formal and informal sector in newborn health in 2010, which can explain the reason that the effect of the ban law is not significant. Therefore, we believe that this policy has been implemented too early and that it is likely to be effective only as the country's economy grows and medical conditions improve.

Meanwhile, we believe that the Malawi government should firstly increase health expenditure in improving the quality of local care level, rather than legislating against informal delivery, which would neither improve the health of newborns and mother nor ease people's heavy healthcare expenses. If there is no significant difference between the formal and informal sectors, this transfer is meaningless and will not have the positive effect that the government expected. Malawi is one of the least developing countries, health expenditure per capita is $35 in 2018 (World Bank, 2018), wasting such valuable healthcare resources on an ineffective policy is a huge waste for the country.

However, although we have not found significant effects of this policy, we remain optimistic about the long-term effects of this policy. Based on experience around the world, the difference in risk between formal and informal deliveries is significant when countries have basic medical facilities with educated doctors and nurses, then the effect of the law compelling people to use formal medical facilities for deliveries would have a significant positive impact on improving maternal and newborn health, therefore, we believe that the effects of this policy will gradually emerge in the long run if the Malawi's health care continues to improve.

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Table and Graph

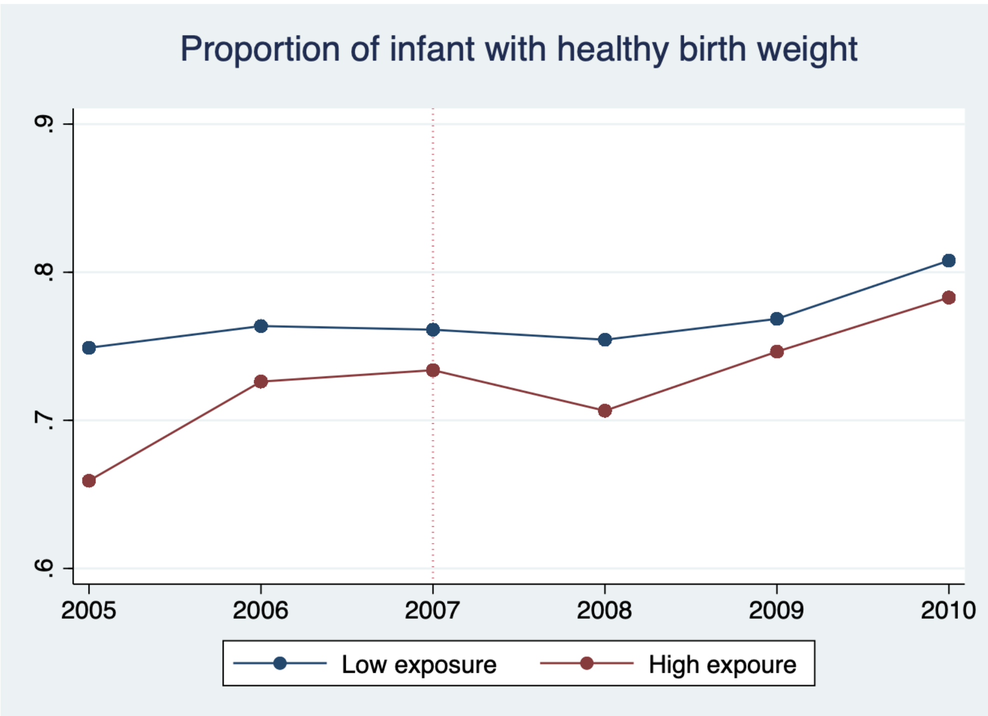


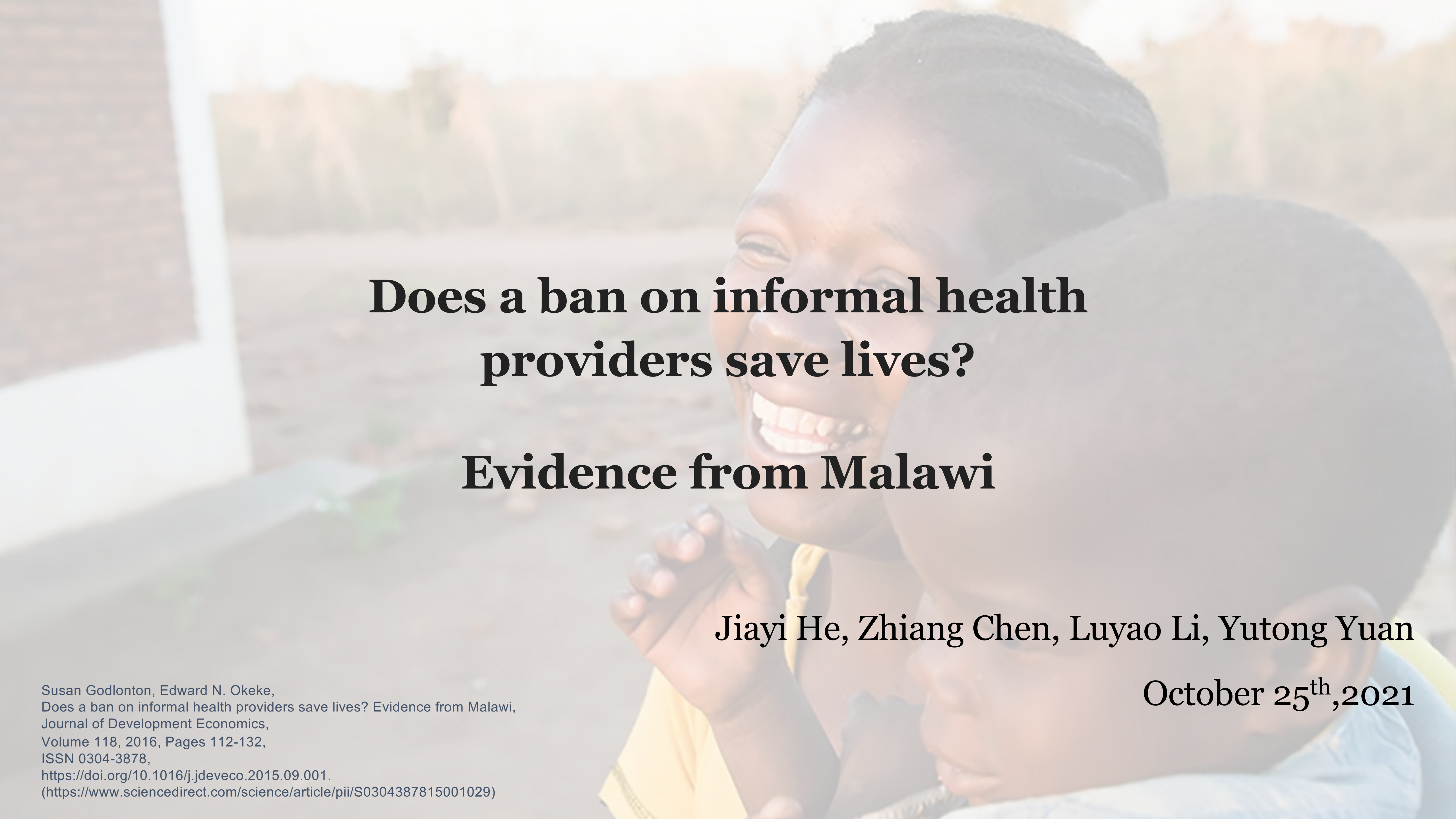
Figure 1: Parallel Trend Assumption for Born with Healthy Weight

Table 1: Estimation Results and Summary Statistics from All Models In The Paper

	Effect of the policy on new born health using difference-in-difference method						Effect of the formal attendant on newborn in 2010				Effect of the formal attendant on newborn in 2015-16			
	(1)	(2)	(3)	(4)	(5)	(6)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
	Newborn baby with healthy weight						Born alive	Born with healthy weight	Dead in one week	Dead in one month	Born alive	Born with healthy weight	Dead in one week	Dead in one month
High	-0.0337**	-0.0224	-0.0253	-0.0288*	-0.0180									
	(0.0159)	(0.0148)	(0.0151)	(0.0159)	(0.0185)									
Post				-0.0487	0.103	0.0947								
				(0.103)	(0.147)	(0.138)								
High X Post	0.00766	0.00669	0.0114	0.0153	0.0144	0.00642								
	(0.0171)	(0.0176)	(0.0192)	(0.0197)	(0.0222)	(0.0196)								
Formal							0.0211	0.0276	-0.00467	-0.0107*	-0.00635	0.0778**	0.000747	0.000464
							(0.0136)	(0.0184)	(0.00470)	(0.00586)	(0.0140)	(0.0342)	(0.00592)	(0.00661)
Constant	0.800***	0.789***	0.791***	-0.0343	-2.060***	0.668***	0.933***	0.763***	-0.00664	-0.000170	1.028***	0.749***	-0.0150	-0.0120
	(0.00203)	(0.0579)	(0.0570)	(0.302)	(0.440)	(0.116)	(0.0410)	(0.0652)	(0.0124)	(0.0186)	(0.0181)	(0.0875)	(0.0138)	(0.0144)
Observations	12,532	11,916	11,916	11,916	7,231	11,916	11,905	11,905	11,905	11,905	11,811	11,811	11,811	11,811
R-squared	0.013	0.023	0.025	0.021	0.028	0.101	0.018	0.023	0.012	0.014	0.013	0.023	0.011	0.010
Controls	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls X Post	No	No	Yes	Yes	Yes	Yes								
District-specific trend	No	No	No	Yes	Yes	No								
Trimmed data	No	No	No	No	Yes	No								
Cluster fixed effect	No	No	No	No	No	Yes								

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 1: Estimation Results and Summary Statistics from All Models In The Paper



Does a ban on informal health providers save lives?

Evidence from Malawi

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Susan Godlonton, Edward N. Okeke,
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CONTENTS

- Introduction: Paper result and our extension direction
- Data resource
- Methods
- Results
- Robustness checks
- Conclusion

Introduction

- Background
  - Malawi has one of the highest maternal mortality ratios globally, currently estimated at **439 maternal deaths per 100k live births in 2021***
- The article investigated:
  - The effect of **a ban on informal (traditional) birth attendants** imposed by the Malawi government in 2007
- The author found and believed:
  - **Not find any evidence** of a statistically **significant reduction in newborn mortality** on average.
  - The findings show **that increasing the use** of formal health providers and facilities **does not lead to significant improvements in health outcomes**

*Source: *USAID website*

Data

- 2010 Malawi Demographic and Health Survey

  -a stratified, two-stage cluster design

  -includes 849 **clusters** (or villages)—158 in urban areas and 691 in rural areas

  -within each selected **household**, women of reproductive age (15–49 years old), and household heads are interviewed

  -women are asked about all births within the preceding five years

- 2015-2016 Malawi Demographic and Health Survey

Strategy

- Difference-in-Difference strategy
  - To estimate the causal effect of the ban on outcomes
  - exploits variation across time and space in the “**intensity of exposure**” to the ban
  - **High-exposure areas***: correspond to a meaningfully high fraction of informal attendant use. We argue that such areas are likely to experience greater enforcement
  - High exposure VS Low exposure area

* Here we assume that a high-exposure village as one where baseline prevalence of informal attendant use exceeds the 75th percentile

Our questions and extensions

- Does this ban law really have NO positive effect on health?
- We consider:
  - Except mortality rate, there are more measurements on health outcome
  - **1. Newborn weight**
  - **2. HIV test result**
  - **3. Newborn alive rate**

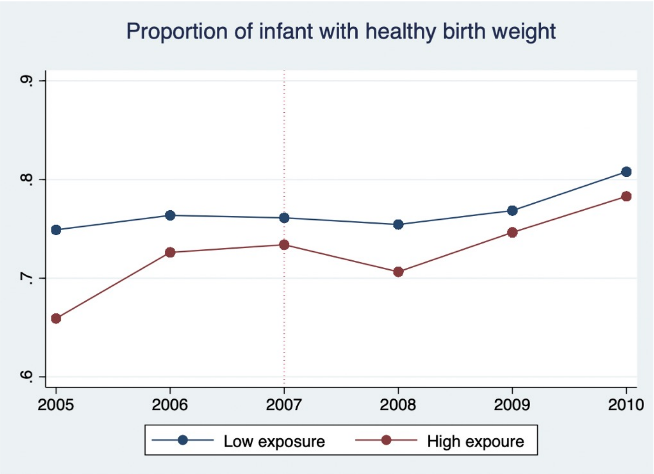
  Does any of them lead to significant improvement on newborn health?

$$Y\_icdt = \alpha_1 + \alpha_2 Post_t + \delta HighExposure_c + \gamma HighExposure_c * Post_t + X_{ict}\beta + \eta_d + \tau_t + \epsilon_{icdt}$$

- Extension 1.1
  - New measurement 1 on health: **Newborn weight**
  - estimate the causal effect of the ban law on Newborn weight
- Extension 1.2
  - New measurement 2 on health: **HIV test result**
  - estimate the causal effect of the ban law on HIV test result
- Extension 1.3
  - New measurement 3 on health: **Newborn alive**
  - estimate the causal effect of the ban law on Newborn alive

1.1 : Newborn Weight

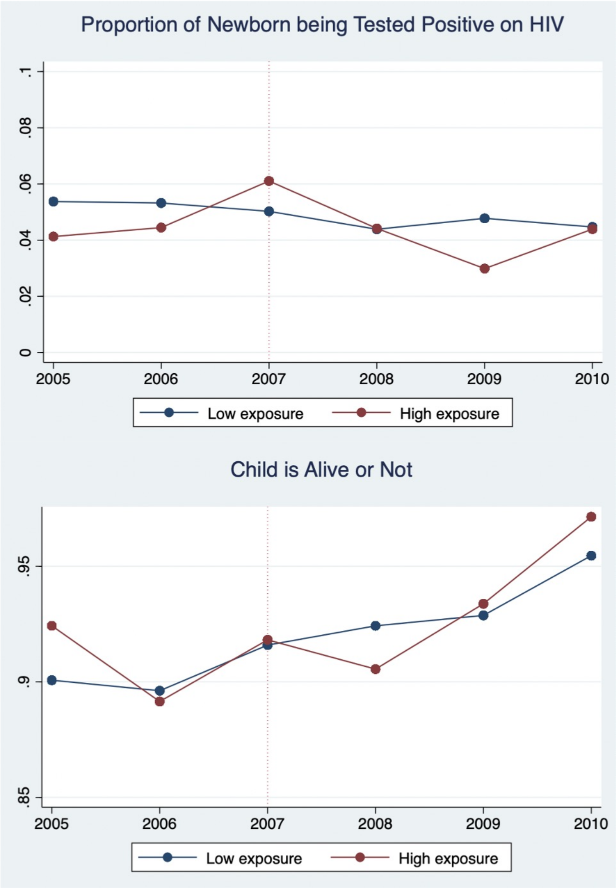
- How was the causal effect of the ban law on newborn weight?
- Based on WHO Child Growth Standards:
  - ➢ girl 2.4kg-4.2kg, boy 2.5kg-4.4kg
- Data we use: m19 (birth weight)
  - ➢ Generate dummy variables for girl and boy
  - ➢ In the healthy range or not
- **Method: DD**
  - ➢ Assumption: Parallel trend
  - ➢ Apply DD in high exposure area and low exposure area
  - ➢ High exposure: treatment group; Low exposure: control group
  - ➢ $\boldsymbol{Y\_icdtW = \alpha_1 + \alpha_2 Post_t + \delta HighExposure_c + \gamma HighExposure_c * Post_t + X_{ict}\beta + \eta_d + \tau_t + \epsilon_{icdt}}$,
- Result: **Increasing the exposure of ban law does not lead to significant improvements in newborn healthy weight level outcomes.**



VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
	Newborn baby with healthy weight					
High	-0.0337**	-0.0224	-0.0253	-0.0288*	-0.0180	
	(0.0159)	(0.0148)	(0.0151)	(0.0159)	(0.0185)	
Post				-0.0487	0.103	0.0947
				(0.103)	(0.147)	(0.138)
High X Post	0.00766	0.00669	0.0114	0.0153	0.0144	0.00642
	(0.0171)	(0.0176)	(0.0192)	(0.0197)	(0.0222)	(0.0196)
Constant	0.800***	0.789***	0.791***	-0.0343	-2.060***	0.668***
	(0.00203)	(0.0579)	(0.0570)	(0.302)	(0.440)	(0.116)
Observations	12,532	11,916	11,916	11,916	7,231	11,916
R-squared	0.013	0.023	0.025	0.021	0.028	0.101
Controls	No	Yes	Yes	Yes	Yes	Yes
Controls X Post	No	No	Yes	Yes	Yes	Yes
District-specific trend	No	No	No	Yes	Yes	No
Trimmed data	No	No	No	No	Yes	No
Cluster fixed effect	No	No	No	No	No	Yes
Robust standard errors in parentheses						
*** p<0.01, ** p<0.05, * p<0.1						

1.2 : HIV test result

- Data we use: s1317 (result of HIV test)
- Method:
  - Assumption: NOT Parallel trend
  - Cannot apply DD



1.3 : Newborn Alive

- Data we use: b5 (child is alive until the survey time)
- Method:
  - Assumption: NOT Parallel trend
  - Cannot apply DD

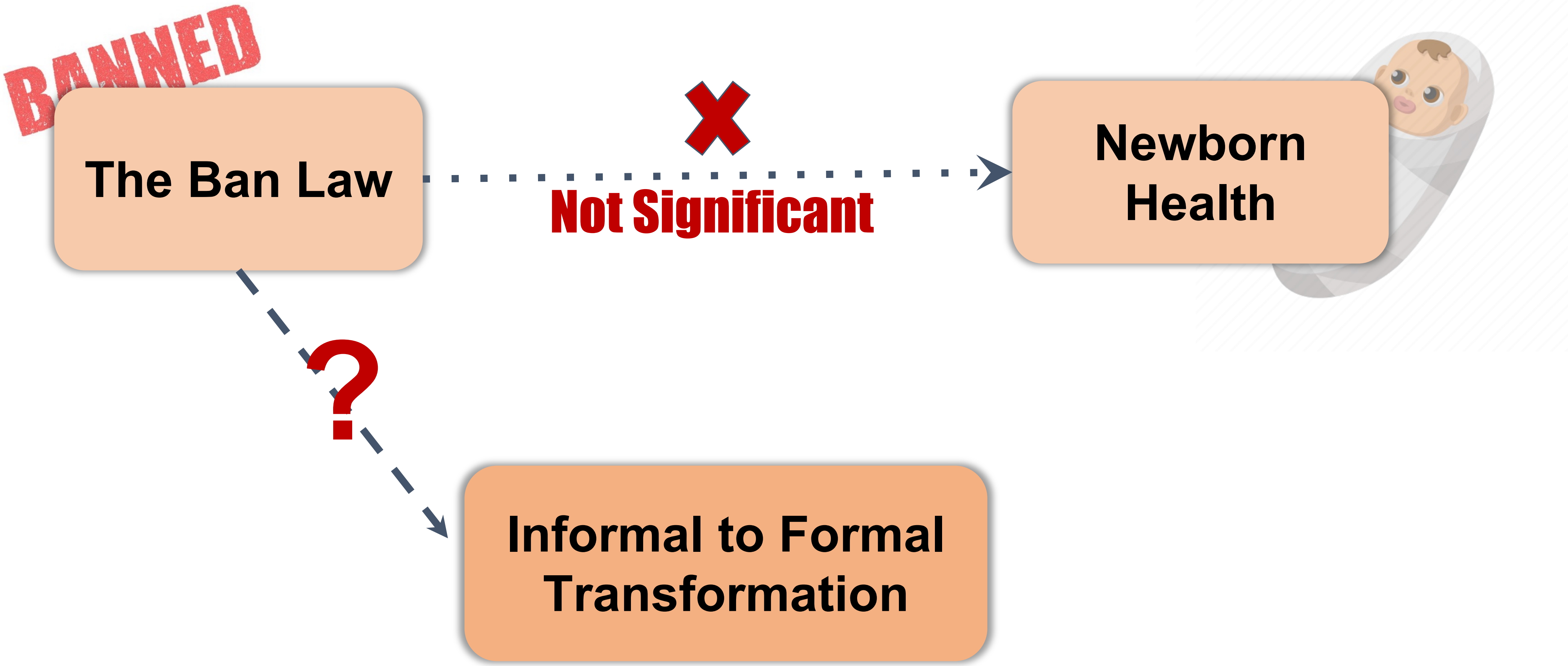
Any other models can be applied to test the ban law effects?

- ~~**OLS Regression**~~ Cannot estimate the causal effect of the ban on outcomes
- ~~**Discontinuous Regression**~~ Can not define the threshold

Extension 1 Conclusion: 3 new health measurements

- **Newborn Weight, HIV Test result, Newborn alive until the survey**
- To estimate the causal effect of the ban on outcomes
- Use Difference in Difference
- Newborn Weight. Not statistically significant improvements in newborn healthy weight level outcomes.
- Cannot measure HIV Test result, Newborn alive
- **Although transform from informal to formal, not statistically significant improvements on health.**

Investigation Mind Map



Transformation

- Results from the Table 5 in the paper use the DD method to estimate the effect of the policy on the **informal attendant** (Panel A) and the **formal attendant** (Panel B).

- Informal attendant decrease by **18.9%**, and formal attendant increase by **14.5%**. The shifting by this policy exists.

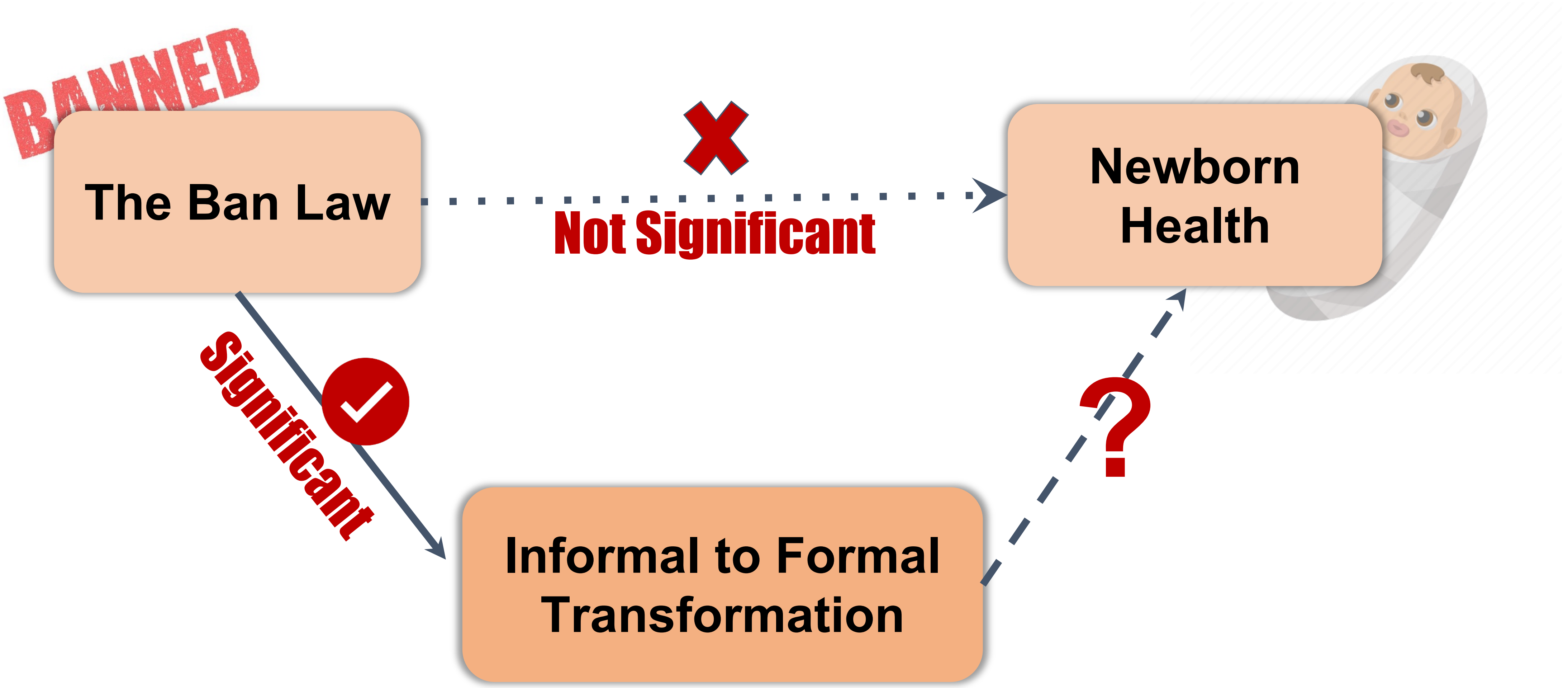
Table 5
What was the effect of the ban on the use of formal and informal sector providers?

Variables	(1)	(2)	(3)	(4)	(5)	(6)
A. Birth attendant is informal attendant						
High exposure × *Post*	−0.189***	−0.190***	−0.184***	−0.187***	−0.154***	−0.188***
	(0.0146)	(0.0130)	(0.0141)	(0.0144)	(0.0126)	(0.0146)
High exposure	0.344***	0.321***	0.318***	0.320***	0.267***	
	(0.0143)	(0.0131)	(0.0123)	(0.0127)	(0.0110)	
Post				0.0134	−0.0655	−0.000915
				(0.0667)	(0.0908)	(0.0679)
Constant	0.0411***	0.0537	0.0512	1.848***	3.525***	0.265***
	(0.00204)	(0.0415)	(0.0410)	(0.284)	(0.440)	(0.0637)
Observations	19,607	18,673	18,673	18,673	12,491	18,673
R-squared	0.138	0.149	0.150	0.148	0.113	0.209
B. Birth attendant is formal sector provider						
High exposure × *Post*	0.145***	0.144***	0.143***	0.146***	0.109***	0.150***
	(0.0157)	(0.0136)	(0.0153)	(0.0152)	(0.0152)	(0.0165)
High exposure	−0.317***	−0.270***	−0.269***	−0.271***	−0.206***	
	(0.0177)	(0.0150)	(0.0152)	(0.0149)	(0.0155)	
Post				0.0660	0.132	0.00746
				(0.0794)	(0.0889)	(0.0974)
Constant	0.808***	0.726***	0.730***	−1.668***	−2.433***	0.446***
	(0.00257)	(0.0431)	(0.0429)	(0.391)	(0.479)	(0.0995)
Controls	No	Yes	Yes	Yes	Yes	Yes
Controls × *Post*	No	No	Yes	Yes	Yes	Yes
District-specific trend	No	No	No	Yes	Yes	No
Trimmed data	No	No	No	No	Yes	No
Cluster fixed effects	No	No	No	No	No	Yes
Observations	19,607	18,673	18,673	18,673	12,491	18,673
R-squared	0.088	0.132	0.134	0.131	0.104	0.218

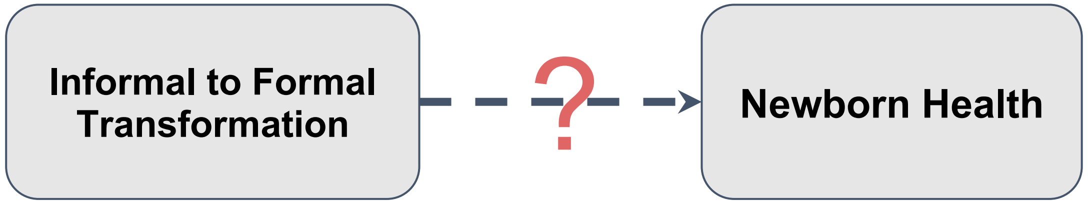
Notes: for Panel A the dependent variable is an indicator for a birth attended by an informal birth attendant. For Panel B the dependent variable is an indicator for a birth attended by a formal-sector provider. Controls include an indicator for male births, an indicator for a multiple birth, birth order, dummies for mother's level of schooling, dummies for mother's age at birth, an indicator for women who are married or living with a partner, dummies for ethnicity and religion, dummies for the partner's educational attainment, distance to the nearest health facility, wealth quintile dummies, and a rural–urban indicator. Each column includes district and year × month fixed effects. Full set of coefficients is not shown to conserve space (see Table A.1). In Column 5, we exclude villages with baseline prevalence of 0 or 1 to account for 'floor' and 'ceiling' effects. Column 6 is equivalent to Column 3 except that district fixed effects have been replaced with cluster fixed effects. *Post* = 1 if birth occurs after December 2007. Standard errors in parentheses are clustered at the district level (there are 27 districts).

*** $p < 0.01$.
** $p < 0.05$.
* $p < 0.1$.

Investigation Mind Map



Extension 2



- The effectiveness of transformation from informal to formal on the children's health level.
- Is there any difference on the quality of medical care between on delivery?
    - Mortality rate within one week
    - Mortality rate within one month
    - Survival until the survey
    - Newborn health by weight

Extension 2 OLS regression

- **Why OLS?**
  - Compared with causality, we care more about the difference between formal & informal sectors.

- **Why not DD, RD or IV?**
  - No parallel trend
  - No threshold
  - No discontinues change
  - No random assignment

- $\boldsymbol{Y_{icd} = \alpha_0 + \alpha_1 * FORMAL_{icd} + \beta * X_{icd} + \epsilon_{icd}}$

  - Y_{icd} the probability of children i in cluster c in district d:
    - Mortality within one week
    - Mortality within one month
    - Survival until the survey
    - Newborn health by weight

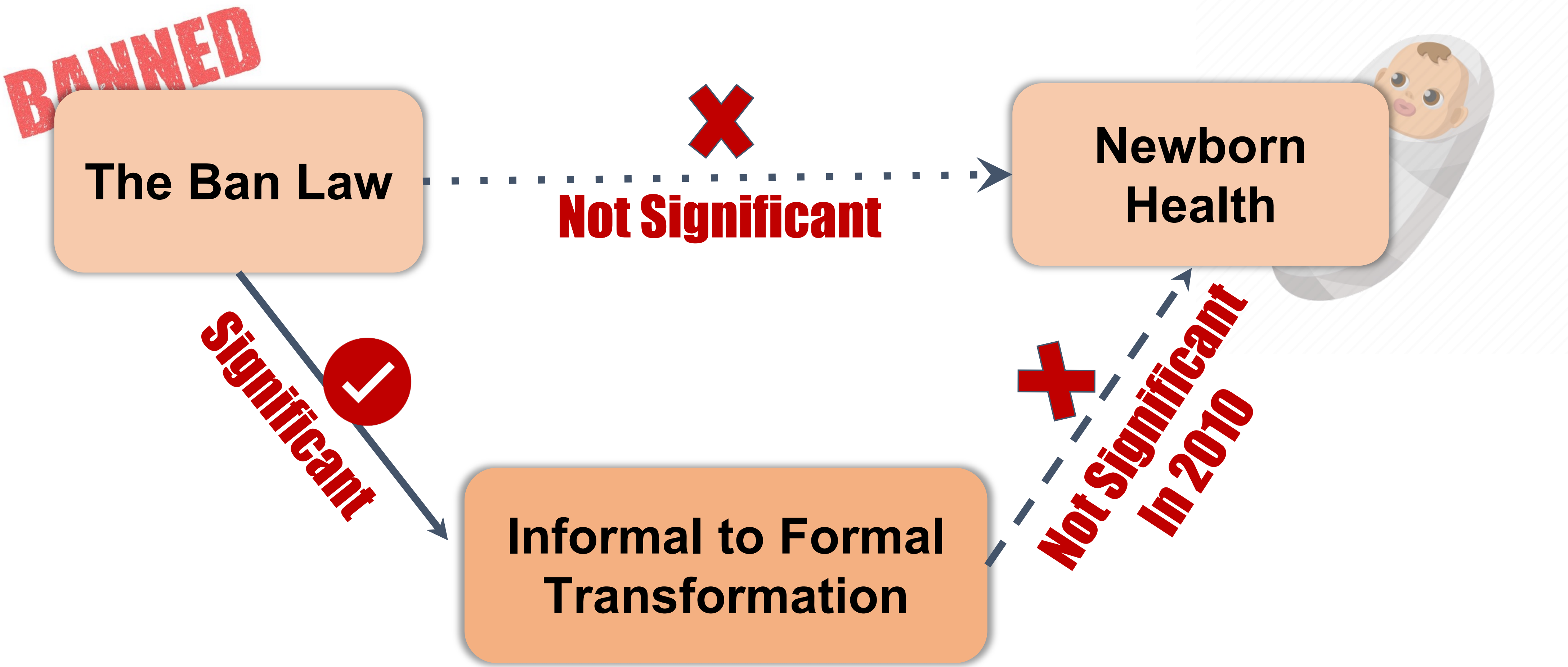
  - $FORMAL_{icd}$ whether the children i in cluster c in district d in born in formal or informal
  - X_{icd} all the control variable including gender, religion, education level, wealth level, district, cluster and etc. for the children i in cluster c in district d.

Extension 2 Results

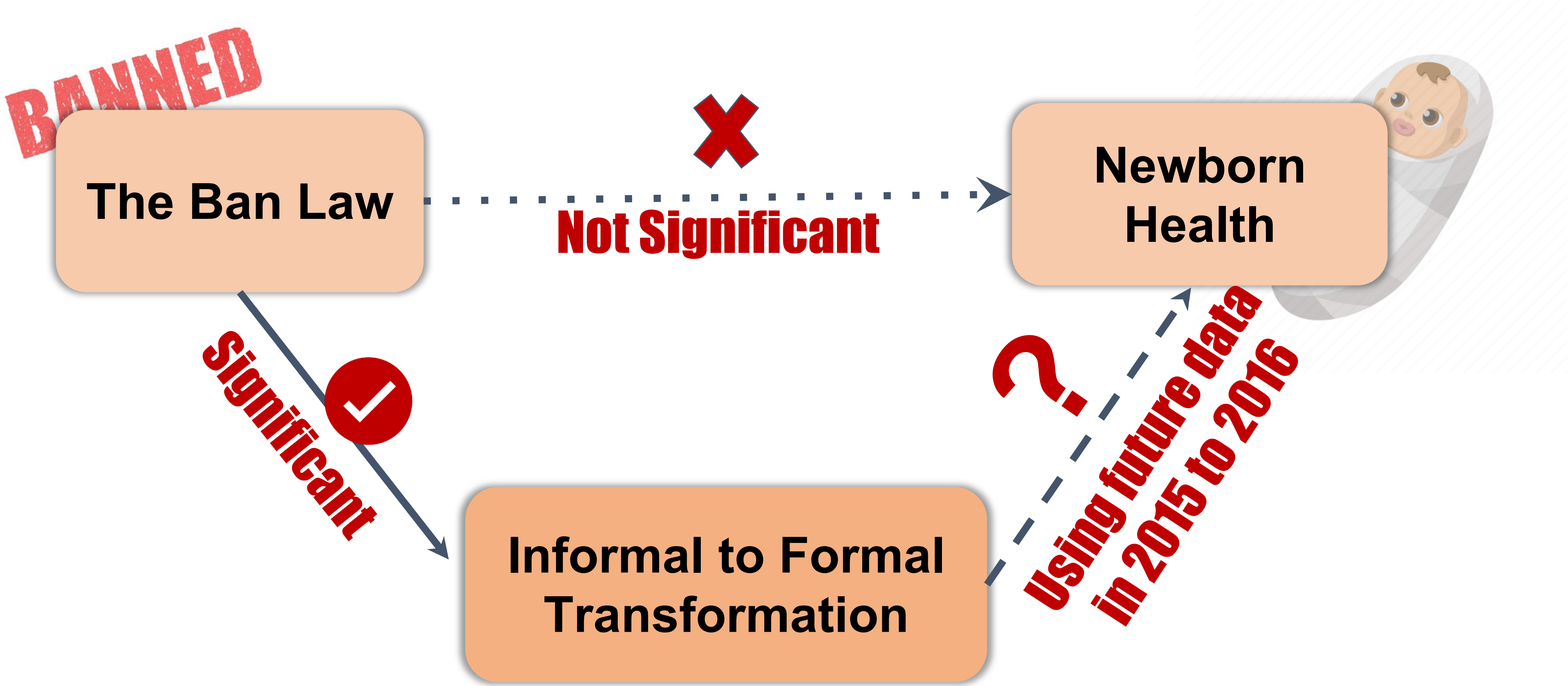
- For all of 4 models, we find no significance on mortality within one week, one month, whether survival until the survey or newborn health by weight.
- There is no statistically difference on the healthcare level between formal sector and informal sector.

	(1)	(2)	(3)	(4)
VARIABLES	Child is alive	Dead in a month	Dead in a week	Born with healthy weight
Use of formal sectors	0.0234*	-0.0104*	-0.00413	0.0324*
	(0.0132)	(0.00595)	(0.00462)	(0.0181)
Constant	0.933***	-0.000687	-0.00828	0.761***
	(0.0417)	(0.0188)	(0.0124)	(0.0652)
Observations	11,905	11,905	11,905	11,905
R-squared	0.009	0.007	0.005	0.016
Control	Yes	Yes	Yes	Yes
Robust standard errors in parentheses				
*** p<0.01, ** p<0.05, * p<0.1				

Investigation Mind Map



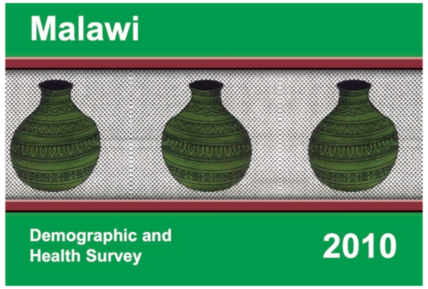
Investigation Mind Map

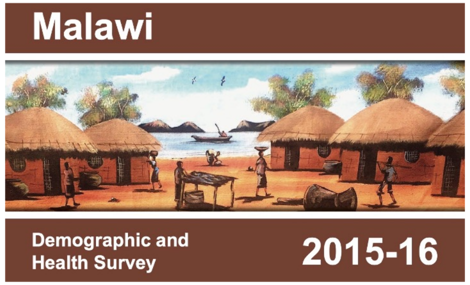


Extension 2 Further Study

- We use the 2010 Malawi Demographic and Health Survey data in our study, at that time the health expenditure per capita in Malawi is US$68, which this number have a **77% increase**.*
- We might argue that as the medical expenditure increase, the difference between formal and informal might also increase.
- The 2015-2016 Malawi Demographic and Health Survey data* will be used.

Current health expenditure per capita in Malawi





*Source: World Bank, https://data.worldbank.org/indicator/SH.XPD.CHEX.PP.CD?end=2018&locations=MW
The DHS Program, https://dhsprogram.com/data/dataset/Malawi_Standard-DHS_2015.cfm

Conclusion

1. No statistically significant nor economically significant impact of policy on the probability of newborn baby having healthy weight.

2. Use of formal sector providers does not affect
- Probability of death within a week
- Probability of death within a month,
- Whether the child is still alive
- Whether a baby is weighted in the healthy range

=> Use of formal sector or not does not make real changes to a baby's health

Limitation

- **Measurement error**
  - dataset is from the 2010 survey, while the ban law was enforced in 2006 => Recall bias
- **Suboptimal Choice of Control and Treatment Group**
  - Districts with low exposure towards the policy is considered as control
  - Households in the control group are somehow exposed to the policy and their behaviors may change due to the policy
- **Omitted Variable Bias**
- **External Validity**
  - Malawi is unique and the result may not generalize

Final Thoughts

- This policy is more of an empty talk right now.
- With poverty issues, and insufficient financial support to the healthcare facilities, banning the use of informal birth attendance could increase the economic burden of the citizens.
- Malawi government should improve its healthcare quality and its infrastructure first.
- In long run, we are optimistic about the impact of the ban on use of informal sectors.