Return on Universal Education: SSA Case Study on Bihar

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Abstract

Mass universal education is a necessary condition for initiation of economic development in underdeveloped and backward state like Bihar in India. The Govt. of India has taken initiative for universal mass education and prime focus is on Sarbha Shikhsha Abhijan (SSA). This study attempts to assess the impact of universal education programme such as SSA in Bihar. The difference –in-difference (DD) approach is used here to measure the impact of SSA treatment on unorganised sector in Bihar. This study finds that literate people earn Rs. 43 higher than that of illiterate, and SSA is giving additional return nearly more than Rs. 600 Crore per annum only from small and tiny enterprise in urban Bihar.

Key Words: DD, Difference –in-Difference, Control group, Treatment, SSA, Universal Mass Education, Bihar, income, Return on Education, unorganised sector, development.

1. Introduction

Education is the cornerstone of economic growth and social development. Schooling is desirable for individual as well as for society. At macro level, a better-educated workforce enhances a nation's stock of human capital that is crucial for raising productivity and economic development (Barro, 1996; Romer, 1986; Lucas, 1988; Ravallion and Chen, 1997). One of the crucial problems of economic development is the problem of accounting for income pattern and related other social issues; one of them is the educational externality (Lucas 1988). There are different opinions regarding the presence of external effect of human capital. However, it is difficult to capture the externality of human capital. In Lucas (1988), human capital is found to have positive external effect on aggregate production function. In the presence of external effect, the social and private return to human capital differs. There exists a substantial empirical literature relating human capital accumulation to economic growth. In 50s and 60s Gary Becker, Jacob Mincer, T.W. Schultz and other economists focus on the role of education on economic development. Recently, Lucas (1988), Barro (1991), Mankiw, Romer and Weil (1992) link education to economic growth and findings of education externalities improve literature on it. The positive externalities associated with human capital are given importance in the new growth theories, and in most of these dynamic models externality result in the returns to scale in the production sector. Basic question here is: How do we measure the educational externalities? Applying difference in difference (DD) approach, this paper attempts to assess the impact of education, especially measuring the returns of education.

Truly, acquiring education is an investment in the sense that one gives up something now in the hope of getting more back in future. For that reason, education is often described as 'human capital', the title of a famous book by Gary Becker. So, spending on education should be considered as the investment. Like all investments, how the future gain compares to the current sacrifice is critical in determining whether education is a good investment or not.

What is the factor motivating individual to determine for acquiring education. The basic assumptions are (i) earning of individual depends on year of schooling; i.e., one individual has *s* year of (post compulsory) schooling, earning is *W(s)*. (ii) Assume there is no direct cost but cost of education is only forgone earnings. (iii) Assume everyone lives forever. So, present discount value (*PDV*) of *s* years of education is:

$$PDV = \int_s^\infty e^{-rt} W(s)dt = \frac{1}{r} W\left(s\right) e^{-rS}$$

Taking log of both sides of the above equation can be written as

$$\log\left(PDV\right) = \log W\left(S\right) - rS - \log\left(r\right)$$

First order condition can be written as $\frac{W'(s)}{W(s)} = r$

Acquiring education up to the point where the increase in log earnings is equal to the rate at which future earnings are discounted.

Suppose all individuals are identical and require different levels of education in equilibrium, then must be the case that $\log\left(PDV\right) = \log W\left(S\right) - rS - \log\left(r\right)$ is equalised for different levels of s. The coefficient on s is the measure of *r* – rate of return to education[1].

Economics scholars have invested much energy in identifying the value of educational investment, to determine whether governments and individuals are investing optimally. Much of this work stems from the work of Becker (1962) that introduced the concept of treating investment in education as a capital investment. Since then research scholars mainly focus on

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[1] From empirical findings it is clear that typical OLS estimates from an earnings function are about 2.2 – 12.8 percent which suggests that education is a good investment.

estimation of the return to education investment[2]. However, estimates of the return vary significantly, depending on the data sets used, the assumptions made and the estimation techniques.

Furthermore, attempts at estimating a single rate of return may not be very informative if returns to education differ by education level, or differ across populations (including by social strata). This may be particularly important for policy responses, but ironically gets masked by methodological debates. Similarly, economists often fail to take into account the risk associated with education investment decisions. Risk may play an important role in an individual's education investment decision, and indeed a government's educational investment level, and should be taken into consideration when testing rationality and optimality of education investment (see Heckman, Lochner, and Todd 2008) and the comprehensive review in Heckman et al. (2006)). In addition, as most cogently argued by Oreopoulos and Salvanes (2011), the return to education may be much wider than the private financial returns that is the focus of so much of the economics literature, and perhaps economics as a profession has allowed a major body of research on the non-pecuniary returns (which may create private returns through externalities that are as great – if not greater – than the direct effect of education on earnings) to become dominated by the other social sciences.

Education is the key treatment that may remove major hindrance of social development and economic growth. Educated workforce enhances a nation's stock of human capital which increases productivity and economic development (Barro 1996; Romer 1986; Lucas 1988; Ravallion and Chen 1997). Education is associated with high rates of return, both private and social. So, schooling is desirable for all. There is an increasing focus on achieving universal primary education in developing countries like India. In this context, primary education has the highest social rates of return in developing countries (Psacharooulos and Patrinos 2004). Is it true in India? How far is it true in backward state like Bihar also? This study attempts to answer this question focusing on universal primary education in Bihar.

The government of India has launched the Sarbha Shikha Avijan (SSA) to improve the literacy level and endeavours to achieve universal primary education since 1987-88. Across states this SSA programme is more or less successful. In this context, especially this paper focuses on Bihar, which is one of the least developed states in India. Recently a high rate of

[2] See, for example, the reviews by Card (1999), Harmon, Oosterbeek, and Walker (2003), and the meta analysis of Ashenfelter, Harmon, and Oosterbeek (1999) for research on private returns to schooling; la Fuente and Ciccone (2003) for research addressing the impact of education on the so-called 'knowledge economy' through growth models; and Acemoglu and Angrist (2001) or Oreopoulos and Salvanes (2011) for research on wider externalities associated with education.

growth is observed and consequently speedy development starts to gain momentum in Bihar. Basic question what is the reason behind it. There are several reasons but one of them is the improvement of education level in Bihar. Has any impact of education on Bihar economy? In other word, what is the return of education in Bihar? How do we measure it?

This study attempts to answer the above questions especially in the context of Bihar. This paper is organised as follows: Section 2 explains the methodological issues. Section 3 describes data. Section 4 analyses results, and finally concludes.

2. Methodology: Difference in Difference Approach

Recently the most popular identification strategy in applied work is the difference in difference (DD) methodology (see Dinda 2015 for details). Application of DD is a very simple random assignment with treatment and comparison. One group is treated with intervention and other is control group. DD is the application of two-way fixed effects model having cross sectional and time series data. So, basically we have pre and post data for group receiving intervention. Suppose treatment intervention occurs at t_i and we observe outcome Y_{t1} at t_1 and post treatment outcome Y_{t2} at t_2. Fig 1 (Fig 1a & Fig 1b) show the treatment effect. Using time series data, true effect is the difference between pre and post observed outcome, i.e., $(Y_{t2} - Y_{t1})$ but actual estimated effect of the treatment is $(Y_b - Y_a)$.

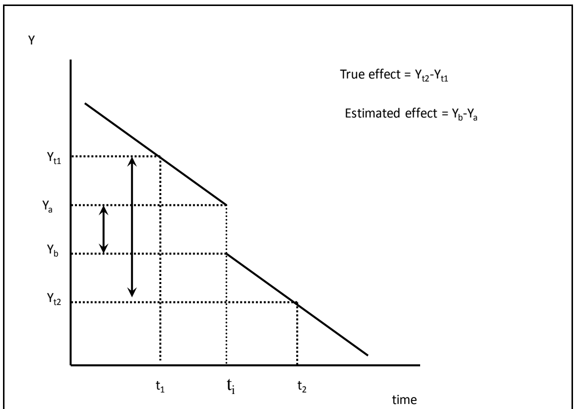


Fig 1a: Pre and Post effects

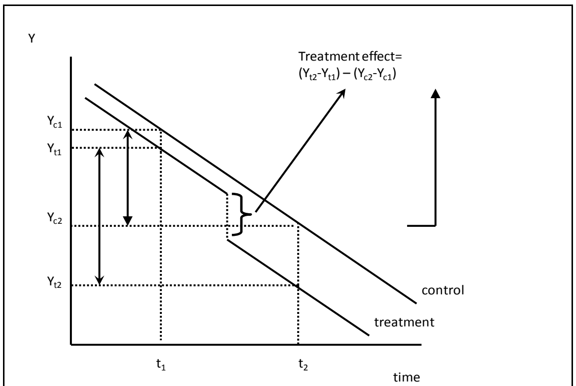


Fig 1b Treatment Effect

We use time series of untreated group to establish what would have occurred in the absence of the intervention. Here, the key concept is the control (c) and treatment (t). Table 1 display the simple calculation of DD approach to measure the impact of treatment.

Difference in Difference

	Before	After	Difference
Group 1 (Treat)	Y_{t1}	Y_{t2}	$\Delta Y_t = Y_{t2}-Y_{t1}$
Group 2 (Control)	Y_{c1}	Y_{c2}	$\Delta Y_c = Y_{c2}-Y_{c1}$
Difference			$\Delta\Delta Y$ $\Delta Y_t - \Delta Y_c$

Table 1: Difference in Difference approach

Control group identifies the time path of outcomes that would have happened in the absence of the treatment. In this example, Y changes by (Y_{c2} – Y_{c1}) even without the intervention. Treatment group identifies the time path of outcomes that would have happened in the intervention of the treatment. In this case, Y changes by (Y_{t2} – Y_{t1}) with the intervention. Here, impact measurement is the difference in the change in outcomes, i.e., (Y_{t2} –Y_{t1}) –(Y_{c2} –Y_{c1}), or, treatment effect is ($\Delta\Delta Y$ =) ΔY_t - ΔY_c .

Fundamental assumption that trends (slopes) are same in treatments and controls. It is true for sometimes. Truly we need minimum three time point observations as depicting in fig 2.

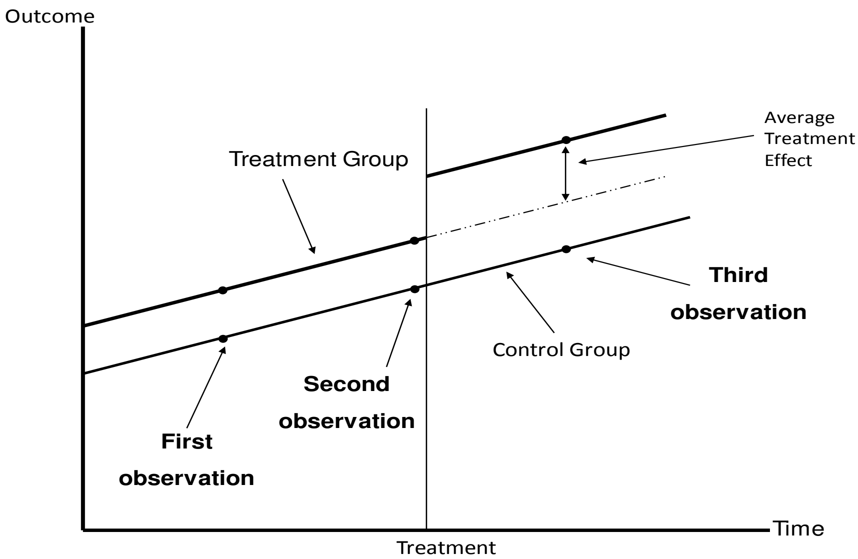


Fig 2: Pre and Post Observations

Following Dinda (2015), We evaluate the impact of treatment or program on an outcome Y over population individuals.

Model

Suppose there are two groups indexed by treatment status T = 0, 1; where 0 and 1 indicate individuals who do not receive treatment (i.e., the control group) and individuals who receive treatment (i.e., treatment group), respectively. Assume that we observe individuals in two time periods, t = 0, 1 where 0 indicates a time period before the treatment group receives treatment (i.e. pre-treatment), and 1 indicates a time period after the treatment group receives treatment (i.e. post-treatment). Every observation is indexed by the letter i = 1,...,N;

individuals will typically have two observations each, one pre-treatment and one post-treatment. For the sake of notation let $\overline{Y_0^T}$ and $\overline{Y_1^T}$ be the sample averages of the outcome for the treatment group before and after treatment, respectively, and let $\overline{Y_0^C}$ and $\overline{Y_1^C}$ be the corresponding sample averages of the outcome for the control group. Subscripts correspond to time period and superscripts to the treatment status.

2.2 Modelling the Outcome

The outcome Yi is modelled by the following equation

$$Y_i = \beta_0 + \beta_1 T_i + \beta_2 t_i + \beta_3 (T_i * t_i) + \varepsilon_i \qquad (1)$$

where the β_0, β_1, β_2, β_3, coefficients are all unknown parameters and ε_i is a random, unobserved "error" term which contains all determinants of Y_i which the model omits. By inspecting the equation we should observe the coefficients and have the following interpretation

β_0 = constant term, β_1 = treatment group specific effect (to account for average permanent differences between treatment and control), β_2 = time trend common to control and treatment groups, β_3 = true effect of treatment

The purpose of the program evaluation is to find a "good" estimate of δ, $\hat{\delta}$, given the data that we have available.

2.3 Assumptions for an Unbiased Estimator

A reasonable criterion for a good estimator is that it be unbiased which means that "on average" the estimate will be correct, or mathematically that the expected value of the estimator

$$E[\widehat{\beta_3}] = \beta_3$$

The assumptions we need for the difference in difference estimator to be correct are given by the following

1) The model in equation (Outcome) is correctly specified. For example, the additive structure imposed is correct.
2) The error term is on average zero: E [ε_i] = 0. Not a hard assumption with the constant term β_0 put in.
3) The error term is uncorrelated with the other variables in the equation:

   Cov (ε_i, T_i) = 0

   Cov (ε_i, t_i) = 0

   Cov (ε_i, T_i* t_i) = 0

the last of these assumptions, also known as the parallel-trend assumption, is the most critical.

Under these assumptions we can use equation (Outcome) to determine that expected values of the average outcomes are given by

$$E[Y_0^T] = \beta_0 + \beta_1$$
$$E[Y_1^T] = \beta_0 + \beta_1 + \beta_2 + \beta_3$$
$$E[Y_0^C] = \beta_0$$
$$E[Y_1^C] = \beta_0 + \beta_2$$

These equations are helpful to identify the estimated impact of a treatment.

2 The Difference in Difference Estimator

Before explaining the difference in difference estimator it is best to review the two simple difference estimators and understand what can go wrong with these. Understanding what is wrong about as an estimator is as important as understanding what is right about it.

2.1 Simple Pre versus Post Estimator

Consider first an estimator based on comparing the average difference in outcome Y_i before and after treatment in the treatment group alone[3].

$$\widehat{\delta_1} = \bar{Y}_1^T - \bar{Y}_0^T \qquad \text{(D1)}$$

Taking the expectation of this estimator we get

$$\begin{aligned} E[\widehat{\delta_1}] &= E[\bar{Y}_1^T] - E[\bar{Y}_0^T] \\ &= [\beta_0 + \beta_1 + \beta_2 + \beta_3] - [\beta_0 + \beta_1] \\ &= \beta_2 + \beta_3 \end{aligned}$$

which means that this estimator will be biased so long as $\beta_2 \neq 0$, i.e. if a time-trend exists in the outcome Y_i then we will confound the time trend as being part of the treatment effect.

2.2 Simple Treatment versus Control Estimator

Next consider the estimator based on comparing the average difference in outcome Y_i post-treatment, between the treatment and control groups, ignoring pre-treatment outcomes[4].

$$\widehat{\delta_2} = \bar{Y}_1^T - \bar{Y}_1^C \qquad \text{(D2)}$$

Taking the expectation of this estimator we get

$$\begin{aligned} E[\widehat{\delta_2}] &= E[\bar{Y}_1^T] - E[\bar{Y}_1^C] \\ &= [\beta_0 + \beta_1 + \beta_2 + \beta_3] - [\beta_0 + \beta_2] \end{aligned}$$

[3] This would be the estimate one would get from an OLS estimate on a regression equation of the form $Y_i = \alpha_1 + \delta_1 T_i + \varepsilon_i$ on the sample from the treatment group only.

[4] This would be the estimate one would get from an OLS estimate on a regression equation of the form $Y_i = \alpha_2 + \delta_2 T_i + \varepsilon_i$ on the post-treatment samples only.

$$= \beta_1 + \beta_3$$

So, this estimator is biased so long as $\beta_1 \neq 0$, i.e. there exist permanent average differences in outcome Yi between the treatment groups. The true treatment effect will be confounded by permanent differences in treatment and control groups that existed prior to any treatment. Note that in a randomized experiments, where subjects are randomly selected into treatment and control groups, β_1 should be zero as both groups should be nearly identical: in this case this estimator may perform well in a controlled experimental setting typically unavailable in most program evaluation problems seen in economics.

2.3 The Difference in Difference Estimator

The difference in difference (or "double difference") estimator is defined as the difference in average outcome in the treatment group before and after treatment minus the difference in average outcome in the control group before and after treatment[5] : it is literally a "difference of differences".

$$\widehat{\delta_{DD}} = (\bar{Y}_1^T - \bar{Y}_0^T) - (\bar{Y}_1^C - \bar{Y}_0^C) \qquad \text{(DD)}$$

Taking the expectation of this estimator we will see that it is unbiased

$$E[\widehat{\delta_{DD}}] = E[\bar{Y}_1^T] - E[\bar{Y}_0^T] - (E[\bar{Y}_1^C] - E[\bar{Y}_0^C])$$
$$=([\beta_0 + \beta_1 + \beta_2 + \beta_3] - [\beta_0 + \beta_1]) - ([\beta_0 + \beta_2]\text{-}\ \beta_0)$$
$$= [\beta_2 + \beta_3] - (\beta_2)$$
$$= \beta_3$$

This estimator can be seen as taking the difference between two pre-versus-post estimators seen above in (D1), subtracting the control group's estimator, which captures the time trend β_2, from the treatment group's estimator to get β_3. We can also rearrange terms in equation (DD) to get $\widehat{\delta_{DD}} = (\bar{Y}_1^T - \bar{Y}_1^C) - (\bar{Y}_0^T - \bar{Y}_0^C)$ in which it can be interpreted as taking the difference of two estimators of the simple treatment versus control type seen in equation (D2). The difference estimator for the pre-period is used to estimate the permanent difference β_1, which is then subtracted away from the post-period estimator to get β_3.

Now, in this context, simple econometrics model is $Y_{it} = \beta_0 + \beta_1 T_{it} + \beta_2 A_{it} + \beta_3 T_{it} A_{it} + \varepsilon_{it}$, where T_{it} is individual treated and A_{it} is in the period when treatment occurs. $T_{it}A_{it}$ is the interaction term, treatment individual after the intervention.

[5] This would be the estimate one would get from an OLS estimate of a regression equation of the form given by (Outcome) on the entire sample.

$$Y_{it} = \beta_0 + \beta_1 T_{it} + \beta_2 A_{it} + \beta_3 T_{it} A_{it} + \varepsilon_{it}$$

	Before	After	Difference
Group 1 (Treat)	$\beta_0 + \beta_1$	$\beta_0 + \beta_1 + \beta_2 + \beta_3$	$\Delta Y_t = \beta_2 + \beta_3$
Group 2 (Control)	β_0	$\beta_0 + \beta_2$	$\Delta Y_c = \beta_2$
Difference			$\Delta\Delta Y = \beta_3$

This DD methodology is used in several studies. Here, we also use the DD for a case study on the return on education in Bihar. For this purpose we collect primary data from a field survey.

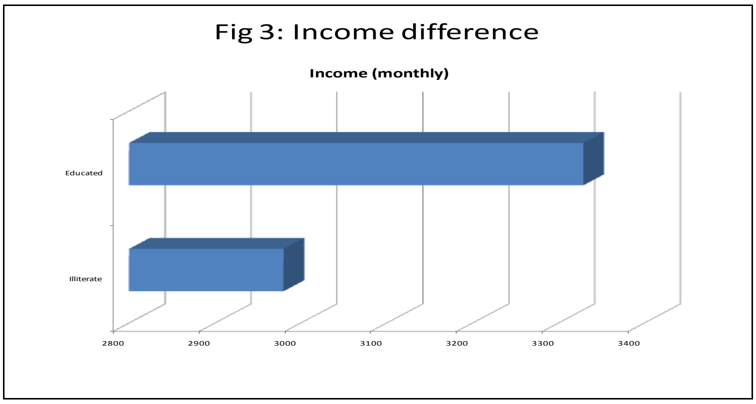
Data

We have collected data on unorganised sector focusing on the small and tinny enterprises covering major urban Bihar during January – July, 2010. The small and tinny enterprises are mostly self-employed (including street vendors) and do their own business as their livelihood. They provide service to the municipal people and contribute to the urban economy. Total number of business unit (population) in this specific unorganised sector in urban Bihar is nearly than 3.5 lakhs. It mainly covers major municipal areas of towns and cities in Bihar. Data are collected in different (three) rounds for cross checking and verifications. So, here, we have a cross section data including thin and densely populated area. Using stratified random sampling technique we have collected data taking several parameters. Finally, our sample size is 2588. These data represent whole urban Bihar covering all districts towns which are consist of words, roads, streets, lane and bye lanes etc.

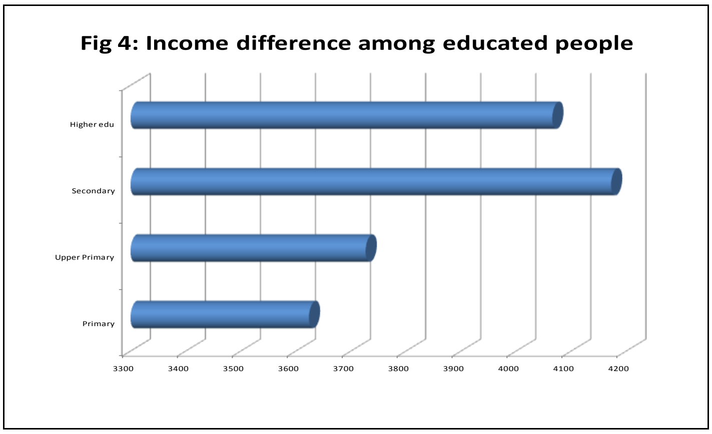
Our main focus is to measure the impact of Sarbha Sikhsha Avijan (SSA) applying difference in difference (DD) approach. Here, we consider that SSA is a treatment which has applied in Bihar since early 1990s. We can apply DD methodology to assess the impact of SSA only having control and treatment groups in pre and post SSA. In this context, we identify and set up illiterate and literate as control and treatment groups, respectively. Individual has reported their age in year. Now, using the 'age' variable we can identify individual weather he/she has received the treatment of SSA or not, and hence we have pre and post SSA groups. SSA starts in early 1990s in Bihar. Hence, individual did not receive SSA treatment if he /she was born before 1988, otherwise, his/her age is more than 22 years and they belong to pre SSA; otherwise belong to post SSA (i.e., age less than 22 years). Literate (treatment) and illiterate (control) individual can be divided into sub-groups according to their age more than 22 years or less such as pre and post control and pre and post treatment SSA. Thus, as per treatment (SSA) and its availability during their childhood we formulate minimum 2x2 groups, i.e., pre and post control as well as pre and post treatment groups in Bihar. Now, we investigate the impact of SSA treatment in Bihar focusing different variables such as income, inequality, etc.

Results

Income of individual is considered here as outcome. For our purpose, we measure the return of SSA treatment. There is a huge income difference between literate and illiterate. Fig 3 shows the monthly income difference between educated and illiterate.



Income also varies among literate people as per their education level. Fig 4 shows the monthly income differences among educated people.



Primary results suggest that literacy drive (or education) has impact on income, but question arises weather impact is significant or not. Now, we examine pair wise *t*-test for income. First we examine alpha *t*- test for income of literate versus illiterate and the alpha *t* is 4.46 and statistically significant. Table 4 displays pair wise alpha *t*-test and their significance levels. Economic returns of secondary and higher education are higher than that of primary education.

Table 4: Alpha t- test

Education Level	Illiterate	Primary	Upper Primary	Secondary
Educated	4.46***			
Illiterate	-			
Primary	2.08**			
Upper Primary	2.69***	0.61		
Secondary	7.46***	3.71***	2.3**	
Higher Education	5.36***	2.06**	1.17	-0.39

Table 5: Difference in Mean Income (daily)

	Age>22years	Age≤22years	
	Before	After	Difference
Treatment (literacy)	128.005	151.15	23.145
Control (Illiterate)	132.26	112.47	-19.79
Difference	-4.225	38.68	**42.935**

Table 5 presents the mean daily income differences using DD approach. Before SSA treatment, average income of literate and illiterate are Rs. 128.0 and Rs. 132.26, respectively. Post SSA treatment, average income of literate and illiterate are Rs. 151.15 and Rs. 112.47, respectively. Mean daily income of literate is Rs. 38.68 more compare to illiterate in the post SSA period. It suggests that on an average daily income of literate people earn Rs. 38.68 more compare to illiterate in the post SSA treatment period. Average daily income of literate people rises by Rs. 23.15 due to SSA treatment. Applying DD approach, average daily income of literate people is higher than that of illiterate due to SSA treatment. Literate people earn on an average daily income of Rs. 42.93 or Rs 43 more than illiterate. Literate people earn more annually Rs 12900 to Rs. 14200 compare to illiterate and estimated additional annual income of Bihar is nearly Rs.645 Crore. Hence, literacy has positive impact on income level of self employed people in the small and tiny enterprise sector in urban economy of Bihar.

Conclusion

This paper attempts to assess the impact of mass universal education programme such as Sarbha Shiksha Abhijan (SSA) in Bihar. Applying difference –in difference (DD) approach, this paper attempts to measure the returns of SSA mass education in Bihar. SSA is giving return more than Rs. 600 per annum only from small and tiny enterprise in urban Bihar. Now, the govt. of Bihar realises the importance of universal primary education and has taken initiative to improve education level, and automatically Bihar economy starts to growth with overall development.

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