On: 22 March 2012, At: 04:54
Publisher: Routledge
Informa Ltd Registered in England and Wales Registered Number: 1072954 Registered office: Mortimer House, 37-41 Mortimer Street, London W1T 3JH, UK

Journal of Development Effectiveness
Publication details, including instructions for authors and subscription information:
http://www.tandfonline.com/loi/rjde20

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Available online: 08 Jun 2011

To cite this article: Maren Duvendack & Richard Palmer-Jones (2011): Comment on: Abou-Ali, H., El-Azony, H., El-Laithy, H., Haughton, J. and Khandker, S., 2010. Evaluating the impact of Egyptian Social Fund for Development programmes. Journal of Development Effectiveness, 2 (4), 521-555, Journal of Development Effectiveness, 3:2, 297-299

To link to this article: http://dx.doi.org/10.1080/19439342.2011.563597

Journal of Development Effectiveness
Vol. 3, No. 2, June 2011, 297–299

DISCUSSION

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Abou-Ali *et al*., in the December 2010 issue of this journal, evaluate the impacts of various activities of the Egyptian Social Fund for Development (SFD) on a wide range of outcome indicators using propensity score matching (PSM). The authors' find that SDF's activities generally have significantly positive impacts (p. 551).

As is well known, PSM results are unreliable in the presence of unobservable variables that are correlated with both programme placement, and / or selection of units into treatment, and capacity to benefit from the intervention (Rosenbaum 2002). Abou-Ali *et al*. use sensitivity analysis to assess the robustness of one of their results (the impact of 'SFD intervention in roads on spending on transportation', p. 543) to selection on unobservables (or 'hidden bias', to use Rosenbaum's terminology). They write that:

> [U]sing a significance cut-off of 10 per cent, we see that [Γ] could be as high as 1.17 before the results lose their statistical significance. . . . In this example, the results are thus relatively robust to hidden bias. (pp. 542–543)

Unfortunately, the opposite is in fact true; the Γ value at which the estimated impact becomes insignificant (that is, $\Gamma = 1.17$) indicates that their results are highly vulnerable to selection on unobservables or 'hidden bias'. This error in the interpretation of sensitivity analysis may not be uncommon, so we will attempt to explain both the correct interpretation and why it is easy to make this mistake.

Rosenbaum (2002, p. 106) developed the conceptual advance of Cornfield *et al.* (1959) that the robustness of the estimate of the difference in outcome between treatment and control groups (the impact estimate) could be assessed by asking what magnitude of selection on unobservables (hidden bias) one would need in order to explain away the observed impact. For example, in the context of death from lung cancer of smokers and non-smokers, Cornfield *et al.* (1959) suggested that if the ratio of the likelihood of death from lung cancer for smokers to the likelihood of death from lung cancer for non-smokers was high,

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ISSN 1943-9342 print/ISSN 1943-9407 online

DOI: 10.1080/19439342.2011.563597
http://www.informaworld.com

then a similarly high ratio for the unobserved characteristic(s) that putatively caused this association would be required to make this unobserved characteristic the true cause of the higher prevalence of death from lung cancer by smokers.

Rosenbaum writes:

> A sensitivity analysis asks: How would inferences about treatment effects be altered by hidden biases of various magnitudes? (2002, p. 106)

And Rosenbaum explains that:

> a sensitivity analysis in an observational study asks how the conclusions of the study might change if people who looked comparable were actually somewhat different . . . (2010, p. 367)

In other words, the objective of sensitivity analysis is to explore whether the matching estimates are robust to selection on unobservables (Caliendo and Kopeinig 2008).

Rosenbaum (2002) invites us to imagine a number Γ (≥ 1), which captures the required ratio of the odds[1] that a unit with the unobserved characteristic, which explains the impact, is selected into treatment compared with the odds that the unit with this characteristic is selected into control, for it (the unobserved characteristic) to explain the observed impact.[2] Thus, Rosenbaum writes:

> A study is sensitive if values of Γ close to 1 could lead to inferences that are very different from those obtained assuming the study is free of hidden bias. A study is insensitive if extreme values of Γ are required to alter the inference. (2002, p. 107)

If Γ is relatively small (say <2), then one may assert that the likelihood that such a characteristic is unobserved is relatively high (it might easily be overlooked), and therefore that the estimated impact is rather sensitive to the existence of unobservables (DiPrete and Gangl 2004). Conversely, if the required ratio of odds is rather large, then it is rather unlikely that it will not have been observed.

For example, in the case of Hammond's (1964, p. 114) observational data on the association of lung cancer with smoking: '[T]he null hypothesis of no effect begins to become plausible . . . with $\Gamma = 6$'. In another discussion of sensitivity analysis, Rosenbaum writes:

> The study [12] of the effects of diethylstilbestrol becomes sensitive at about $\Gamma = 7$, while the study [15] of the effects of coffee becomes sensitive at $\Gamma = 1.3$. A small bias could explain away the effects of coffee, but only an enormous bias could explain away the effects of diethylstilbestrol. (2005, p. 4)

This (and the equivalent passage in Rosenbaum 2002, pp. 104–105 and 112–117) could hardly be clearer. However, the confusion may arise because of the way sensitivity analysis is explained in key texts. Rosenbaum (2002) comments that in a randomised trial $\Gamma = 1$, which is true because, by definition, if randomisation has been achieved, unobserved characteristics have no influence on selection into treatment. This, we suspect, combined with the availability of the readymade *rbounds* software[3] (for Stata and R) to conduct the test, may lead some readers to treat the Γ reported as a test statistic, and conclude that a value of Γ at which results become insignificant that is close to one indicates that the results approximate those of a randomised control trial. However, this is not the correct interpretation, as a slightly more careful reading of this and related texts would indicate.

Abou-Ali *et al*.'s paper is the only study we know of in the area of development that applies sensitivity analysis to PSM, which is highly commendable, as urged by Ichino *et al.* (2006); however, it would be better still if they were to get their interpretation right.

Notes

1. Odds, which are widely used in assessing probabilistic outcomes, are derived from probabilities ($0 \leq \pi_i \leq 1$) by the following formula: $\pi_i / (1 - \pi_i)$.
2. Suppose two individuals j and k who are closely matched on observables so that $x_j = x_k$, but for whom π_j, the probability of j being selected into treatment, is not equal to π_k; that is, the probability of being selected into a programme is not the same for these individuals despite being equivalent on observables. The probability of being selected can be expressed as an odds ratio (the odds of probability of j / k (π_j / π_k) being selected π_j / $(1 - \pi_j)$ or π_k / $(1 - \pi_k)$). Then imagine there is a number Γ (gamma) such that $1 / \Gamma \leq \{\pi_j(1 - \pi_k)\} / \{\pi_k(1 - \pi_j)\} \leq \Gamma$; then if $\Gamma = 1$, $\pi_j = \pi_k$ (that is, there is no difference in the odds of being selected). $\Gamma = 2$ means that individual j is twice as likely to be selected into a programme as individual k.
3. There are other commands developed for Stata to implement sensitivity analyses such as *mhbounds* (developed by Becker and Caliendo 2007) or *sensatt* (Nannicini 2007).

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