Economics Working Papers

2013-27

Simulating publication bias

Martin Paldam

AARHUS UNIVERSITY
BUSINESS AND SOCIAL SCIENCES
DEPARTMENT OF ECONOMICS AND BUSINESS

13/12 2013

Simulating publication bias

Martin Paldam, Department of Economics and Business, Aarhus University, Denmark[1]

Abstract:

Economic research typically runs *J* regressions for each selected for publication – it is often selected as the 'best' of the regressions. The paper examines five possible meanings of the word 'best': *SR*0 is *ideal* selection with no bias; *SR*1 is *polishing*: selection by statistical fit; *SR*2 is *censoring*: selection by the size of estimate; *SR*3 selects the optimal *combination* of fit and size; and *SR*4 selects the first *satisficing* result. The last four *SR*s are steered by priors and result in bias. The MST and the FAT-PET have been developed for detection and correction of such bias. The simulations are made by data variation, while the model is the same. It appears that *SR*0 generates narrow funnels much at odds with observed funnels, while the other four funnels look more realistic. *SR*1 to *SR*4 give the mean a substantial bias that confirms the prior causing the bias. The FAT-PET MRA works well in finding the true value.

Keywords: Meta-analysis, selection of regressions, publication bias

JEL: B4, C9

Acknowledgements:

The simulation program was written in stata by Jan Ditzen, who is a true expert.

1. Street address: Fuglesangs Allé 4, Building 2632 (L), DK-8210 Aarhus V. E-mail: mpaldam@econ.au.dk.
URL: http://www.martin.paldam.dk, for project add /Mpapers-method.php.

1. Introduction: Selecting the top of the iceberg

Empirical economic research has the iceberg property: The visible top is the published regressions, which are selected from all regressions run. Their number follows from the incentives and cost structure in research (see Paldam 2013a). While the visible top of an arctic iceberg is a random sample of the whole berg, this is unlikely to be the case in economics.

This paper reports a set of simulations of this situation. First J estimates of the same parameter are made. Then five formal rules are used to select one of the J estimates. It is shown that rules selecting the 'best' estimate give substantial bias in the reported result. It is also shown that when enough selected estimates are analyzed, the tools of meta-analysis allow us to adjust the mean for the bias to reach a rather precise estimate of the true value.

Section 1.1 is a short introduction to the meta-tools used, while section 1.2 gives a sketch of the simulation method used.

1.1 Tools of meta-analysis in a nutshell:[2] *Funnel, mean, variation, FAT and PET*

The β-literature is all papers that contain estimates b of the parameter β. All N published estimates, b_i, constitute the B-set. When the B-set is coded level one of the meta-analysis is easy to make: From the standard errors, s_i, follow t-ratios, $t_i = b_i/s_i$, and precisions, $p_i = 1/s_i$. This gives the data for the basic meta-analysis: (b_i, s_i, t_i, p_i) for $i = 1, \dots, N$.

The funnel is the (b_i, p_i)-scatter. It has the form showed on Figures 5 to 9 below. It is widest for low p's, and narrows as p increases. If all regressions made are published, the funnel is as lean as implied by the t-ratios and symmetrical. This is unlikely to be the case if the published results are selected as the 'best' of many estimates.

The B-set has the (arithmetic) mean, $\underline{b}$, and the Std that gives, μ = Std/$\underline{b}$, the coefficient of variation, which measures the width of the funnel. In addition the FAT-PET is estimated. The FAT is the funnel asymmetry test, β_F, and the PET is the meta-average, β_M, which adjusts the mean for the most common asymmetry, see section 2.4. For each funnel the *output-set* is $(\underline{b}, \mu, \beta_F, \beta_M)$. The publication bias is the difference: $PB = \underline{b} - \beta$. To test the PET, $PB_{PET} = \beta_M - \beta$ is also calculated. When PB is substantial, PB_{PET} is always much smaller.

1.2 The effect of selection rules on simulated funnels with a known β

The paper studies a set of five formal rules (SR0) to (SR4) to select b from J (= 1, 5, 10, 15,

2. See the recent textbook (Stanley and Doucouliagos 2012) and the guidelines (Stanley *et al.* 2013).

25, 34, 50) simulated regressions. One experiment consists of J regressions for R = 100 funnels with N = 500 points, so RN x J = 50,000 x J regressions are simulated. Within one experiment the five *SR*s are applied to each set of J estimates, so the *SR*s are directly comparable. The *SR*s are analyzed by their effects on the funnel, the output set, and the publication bias.

The five selection rules are: (*SR*0) *ideal* selects the average $\underline{b}_J$ over the J estimates. The other four *SR*s are optimal rules that select by the fit and size of the estimate: (*SR*1) *Polishing* selects by fit; (*SR*2) *Censoring* selects by size; (*SR*3) *Combination* selects by the researcher's indifference map for both fit and size; and (*SR*4) *Satisficing* selects the first result exceeding some value for both criteria. The selection rules (*SR*1) to (*SR*4) give the funnels asymmetries and a substantial publication bias.

Polishing comes from the clarity-prior of the profession demanding statistical significance. Censoring comes from size-priors about β, which are generated by priors at a deeper level: (i) predictions from economic theory; (ii) moral/political considerations; (iii) interests of sponsors; and (iv) prior results of the author or his group.

The paper assumes that the deep prior is from (i). All researchers of β have studied economics, so their theoretical priors about β are likely to be similar. Thus, it is a main prior. Such priors are often for the right sign. For ease of presentation the paper assumes that the main prior is: $\beta > 0$. It is also assumed that the prior is true, so that it is easier to reach a positive than a negative estimate of β though negative estimates do occur.

From Doucouliagos and Stanley (2012) we expect that this prior leads to an exaggeration in the direction of the bias. Thus, we expect that the bias in the mean is positive as indeed it is, see Figure 10 in section 5.1. Thus, the prior gives a confirmation bias.

In practice the variation between results in the β-literature is caused by both data and model variation. The simulations consider data variation only, but then they are varied considerably. Different authors use different *J*s and *SR*s, so the observed bias is a murky average. To get tractable results the simulations look at the extreme case where all papers use the same J and *SR* for each funnel generated.

Section 2 defines and illustrates the five selection rules. Section 3 describes the simulation setup, while section 4 shows how each selection rule works with the seven values of J. Section 5 compares the results from the selection rules, while section 6 concludes. The Appendix lists the definitions used and the parameter choices in the simulation experiments.

2. Selection and publication bias and five selection rules

Section 2.1 discusses the relation between selection and publication bias. Then the five *SR*s, selection rules, are defined. Section 2.2 presents the ideal selection *SR*0, which is the average. Section 2.3 looks at *SR*1 polishing. Section 2.4 considers *SR*2 censoring. Section 2.5 shows that *SR*1 and *SR*2 give different results in practice. Section 2.6 presents *SR*3 that mimics the combined selection; and finally section 2.5 considers *SR*4 satisficing selection.

Note that underlined variables are (arithmetic) means.

2.1 Selection and publication bias

The total number of regressions made in the β-literature is:

(1) $N\underline{J} = \sum_{i=1}^{N} J_i$, where N is the published estimates, while $N(\underline{J} - 1)$ is hidden.

Each b_i published is selected from the J_i-set of regressions done. The (arithmetic) *means* $\underline{b}_{Ji}$ and $\underline{b}_N$ for the J_i-set and the B-set respectively are:

(2) $\underline{b}_{Ji} = \sum_{j=1}^{J_i} b_j / J_i$ and $\underline{b} = \sum_{i=1}^{N} b_i / N$. The selected estimate b_i has the selection bias:

(3) $SB_i = b_i - \beta$, so $b_i = SB_i + \beta$. With a positive main prior SB_i which is positive as well.

The B-set of published estimates has the publication bias:

(4) $PB = \underline{b} - \beta = \sum_{i=1}^{N} b_i / N - \beta = \sum_{i=1}^{N} (SB_i + \beta) / N - \beta = \sum_{i=1}^{N} SB_i / N = \underline{SB}$

The publication bias is thus the mean of the selection bias for all b_i's. Though this is an obvious result, it is important. It means that when a publication bias is found the average selection is biased. The typical β-literature is done by many independent researchers. If they have enough different priors, the selection biases may even out and leave only a small publication bias, but main priors matter for the publication bias.

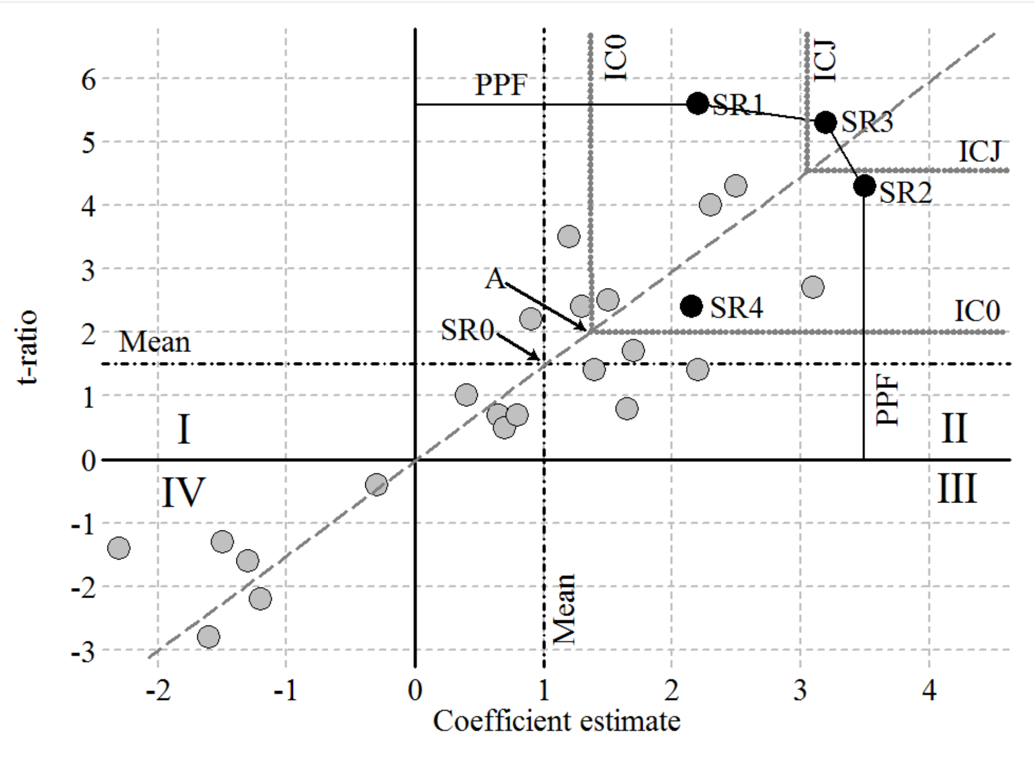
2.2 Figure 1 and the reference point SR0 of an unbiased selection

Figure 1 is a stylized example of J = 25 estimates, shown as a (b, t)-scatter, which illustrates the 5 *SR*s. The figure is explained as we go along. After each section explaining an *SR*, the reader should check the relevant point on the figure.

The two axes on Figure 1 divide the plane in the 4 quadrants: I, II, III and IV. Quadrant I and III are empty by definition, and quadrant IV has wrong signs. The priors of the researcher are for positive *b*’s, which have positive *t*’s. Consider any ray from origo into quadrant II: The longer one gets from origo, the ‘*better*’ is the result by both priors; i.e., the estimate of *b* is further away from zero and it is more significant. Thus, the system of rays defines the direction of better/worse that is used below.

The *SR* chooses one of the *J* points. The choice can be formulated in the familiar PPF/IC terminology. The (*b*, *t*)-results are treated as a ‘production’. The PPF-curve on Figure 1 is the Production Possibility Frontier. All points are ‘worse’ (closer to origo) than a point on the PPF. The ICs are the indifference curves of the researcher.[3] The optimal choice of the researcher is the kink-point on the PPF that touches his utmost (and hence best) IC. The PPF-curves move out as *J* rises. This gives an expansion path that is assumed to be a ray.

Figure 1. A typical example of J = 25 regression estimates of β



Note: Drawn for β = 1. The mean estimate is $\underline{b}$ = 1.01 ≈ β, while the mean t-ratio is $\underline{t}$ = 1.51, as indicated by the two ‘Mean’ lines. If the data sample is m = 40, the t-ratio should exceed 2 at the 5 % level of significance for the two-sided test. See text section 2.2. The J = 25 points are divided in one visible and 24 hidden ones.

3. The analysis considers vertical, horizontal and L-formed IC-curves. When the indifference curves are L-formed as drawn by IC0 and ICJ, it is assumed that the kinks are on the expansion ray.

Imagine a researcher who has no priors at all, or more likely, a researcher who is 'ultra-honest' and manages to suppress his priors. He reports the average of the *J* regressions and some measure of their variance. Thus, the central result for an unbiased researcher is the one termed *SR*0 on Figure 1. In the simulations it is close to the true value of β by design.

Note that this *SR*0 is inside the PPF-curve, so it is not an 'optimal' choice.

2.3 SR1, polishing is selection by the highest t-ratio

Two factors enter into this *SR*:

(i) The *prior for clarity* afflicts all of us. It is unsatisfactory to work long and hard with a problem and come up with wishy-washy results. We feel that we did not learn much if an article reports unclear results, and we do not recommend it to our colleagues. Journals want to publish articles that are read, etc. (ii) The profession is greatly concerned about *statistical* significance, even at the expense of economic significance.[4]

Imagine a researcher who has found a theoretically satisfactory model giving an estimate *b*, which he believes to be a good estimate of β, but where *b* is insignificant. Polishing means that he searches for a model variant close to the good model that increases the fit of *b*. That is, he makes the *J* experiments to find an estimate with a good t-ratio. The selection rule in the polishing case is thus by the *t*-ratio and independent of the size of *b*.

> ***SR*1**: Select the *b* with the highest *t*-ratio. In the PPF-IC terminology the indifference curves are *horizontal* lines. The optimal point chosen on the figure is thus *SR*1, which is larger than 1, as is also demonstrated in column (2) of Table 2 below.

With no polishing the numerical value of the *t*-ratio is proportional to the log of the degrees of freedom. This led Card and Krueger (1995) to propose the MST to detect polishing.

(5) MST: $\ln|t_i| = \tau_S + \tau_P \ln df_i + u_i$, where $\tau_P = ½$ is the H0 of no polishing.

Below it is shown that the test works rather well, but not better than the FAT-PET MRA that gives import and additional information as discussed in section 5.4. Thus, the MST has been encompassed, see Stanley and Doucouliagos (2012; p 77-78) for an assessment.

4. It is not uncommon to read papers where the statistical significance of the coefficients is stressed, but where it is left to the reader to find out what the coefficients mean. D.N. McCloskey has argued that the preference for statistical over economic significance is harmful (McCloskey 1998). She certainly has a point, but the argument has had little apparent effect, and it has got increasingly loud, see Ziliak and McCloskey (2008). Perhaps the argument should be that statistical significance is a necessary condition only.

2.4 *SR2, censoring is selection by the largest size of the estimate*

The introduction made the assumption that the main prior in the profession is that $\beta > 0$. This means that most researchers will discriminate against negative values. And there is a tendency to select relatively large positive values. *SR*2 takes this idea to the extreme:

> ***SR*2**: Select the largest b in the J-set. In the PPF-IC terminology the indifference curves are *vertical*. The optimal point on the figure is thus *SR*2, which is larger than 1, as shown in column (2) of Table 3 below.

This *SR* is easy to solve analytically, as done in Paldam (2013a).[5] The results reached by the simulations are fully in accordance with the analytical solutions. The simulations are run to make the results as comparable as possible to the results from other *SR*s. To handle censoring Stanley (2008) developed the FAT-PET and showed it was a good estimate of the true value:

(6) FAT-PET:[6] $b_i = \beta_M + \beta_F s_i + u_i = \beta_M + \beta_F / p_i + u_i$ where b_M is the PET meta-average and β_F is the FAT, which indicates censoring if $\beta_F \neq 0$. The estimate uses:

(6b) $t_i = \beta_M p_i + \beta_F + v_i$, reached after a division of (6) by s_i.

The FAT-PET consists of two parts: The FAT, and the PET estimate of the meta-average. Many simulation experiments have been made to see how (6) behaves under different circumstances; see Stanley (2008) and Callot and Paldam (2011) and Paldam (2013b). It is clear that the FAT is a powerful test for asymmetry. The PET works well if the bias is a censoring bias, but with other biases it may fail to work. Hence, the PET bias is reported:

(7) $PB_{PET} = \beta_M - \beta$

2.5 *Are polishing and censoring the same?*

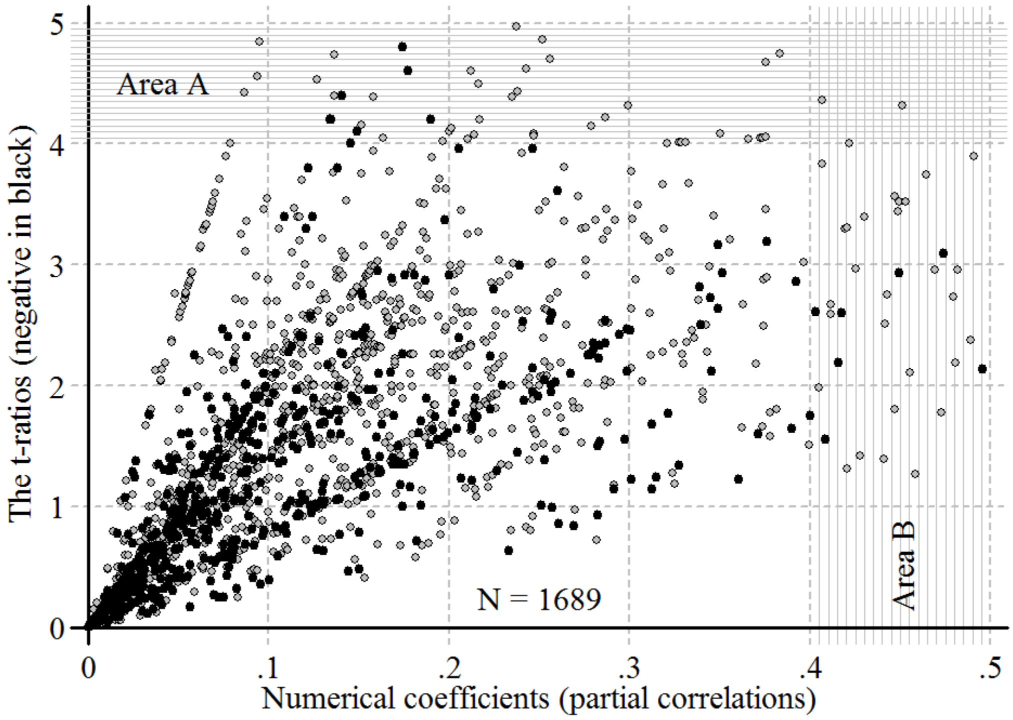
Polishing is often seen as fairly innocent, while censoring gives a substantial bias. The simulations below show that they give much the same bias. However, the stylized example on Figure 1 shows that *SR*1 and *SR*2 give different results, but this may be due to the construction of the example. However, Figure 2 shows the $(|b_i|, |t_i|)$-scatter of the estimates in the AEL, development aid effectiveness literature, that has a substantial publication bias.

---

5. The solution assumes that the J-set is normally distributed, and then uses the inverse to the cumulative normal distribution to calculate the largest of J observations.

6. The FAT is the funnel asymmetry test (from Egger *et al.* 1997) of (H0 no asymmetry: $\beta_F = 0$) and the PET is the precision estimate test (H0 no genuine effect: $\beta_M = 0$). Since $\beta = 1$, our tables should test the H0: $\beta_M = 1$.

Figure 2. The scatter of the numerical values of the results in the AEL



Note: The AEL is the Aid Effectiveness Literature. Until 2010 it had reported 1689 points depicted, see the URL: http://www.martin.paldam.dk/Meta-AEL.php. 90 observations are outside the frames of the graph. The figure uses the same format as Figure 1, but all values are numerical to compress the graph. The negative observations are marked in black. The correlation of the two variables shown is 0.635. The data are analyzed in Doucouliagos and Paldam (2008, 2011 and 2013).

*SR*1 and *SR*2 would have given the same results if the scatter of (b_i, t_i)-pairs were lying on one proportionality ray through origo. The figure contains many points that look as if they are on proportionality rays, but these rays have different slopes.

Area A contains the observations with the highest t-ratios (between 4 and 5). It is shaded with horizontal lines. It is likely that these 43 observations are selected by a polishing *SR*. Area B contains the observations with the highest coefficients (between 0.4 and 0.5). It is shaded with vertical lines. It is likely that these 39 observations are selected by a censoring *SR*. Only 3 observations are in the checkered area where the A and B areas overlap. Thus, the example suggests that the two selection rules lead to different outcomes.

In the simulations in section 3 the selection rules give rather similar results, especially for the low values of *J* such as 5 and 10. This is a problem which is probably due to the fact that all experiments are with data variation, and not with model variation.

2.6 SR3, selection of the best (b_i, t_i)-mixture

From introspection I think that researchers look for the estimate that is best by some mixture of size and fit. Thus, I want to use more realistic indifference curves, i.e., ICs, which bend. To make the results simple and tractable, three sets of assumptions are made.

The researchers have read the literature and know that they should find a b that is as large as everybody else. Also, b should be significant. Thus, the acceptance point is $(b_A, t_A) = (1.25\beta, 2)$.

(i) The ICs have one bend at the expansion path; i.e., they are L-formed. They are vertical to one side and horizontal to the other, as drawn by the IC0 and ICJ curves.

(ii) The expansion path is a ray. It starts at the origin and it is fixed by one more point: The minimum acceptance point A is (b_A, t_A). Thus, the expansion ray is:

(iii) $t = \lambda_A b$, where the slope $\lambda_A = t_A/b_A = (b_A/s_A)/b_A = 1/s_A = p_A$, so that point A = (s_A, p_A).

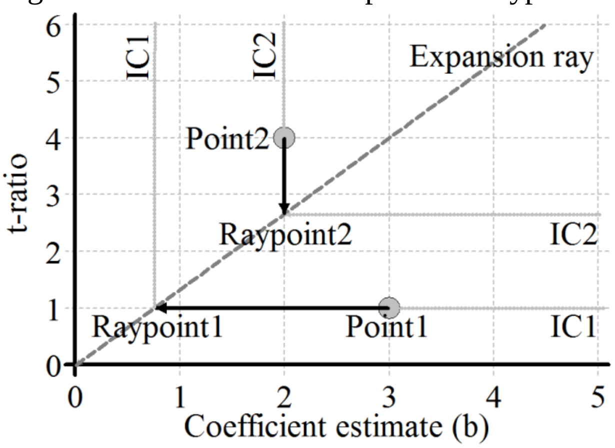
Figure 1 shows point A and the expansion ray. It is drawn as the dashed gray line. The IC0-curve has a kink in A. ICJ is the first indifference curve that contains one point only. It is easy to calculate: First all *J points* in the *J*-set are converted to *raypoints* on the expansion ray. Think of the point (b_j, t_j), as illustrated with two points on Figure 3.

(8a) The horizontal distance to the expansion ray is: $h_A = b_j - s_A t_j$, at the point $(s_A t_j, t_j)$.

(8b) The vertical distance to the expansion ray is to the point $(b_j, p_A b_j)$.

If $h_A \leq 0$ the raypoint is (8a), and if $h_A > 0$ the raypoint is (8b). Thus, the *bj*-set is converted to raypoints. *SR*3 is the point on Figure 1 with the utmost raypoint.

Figure 3. The conversion of points to raypoints



Note: Drawn as a part of Figure 1. The ray has the slope 4/3, so p_A = 4/3 and s_A =3/4. Point1 is (1, 3) so the horizontal distance to the ray is negative and Raypoint1 is $(s_A t_j, t_j)$ = (1, 1(3/4)) = (0.75, 1). Point2 is (2, 4,) so that the horizontal distance to ray is positive and Raypoint2 is $(b_j, p_A b_j)$ = (2, (4/3)·2) = (2, 2.67). Here Raypoint2 is the preferred point as IC2 is further from origo than IC1.

***SR*3**: Select the last point inside the outmost indifference curve, which has its kink at the utmost raypoint. The optimal point on Figure 1 is thus *SR*3, which is larger than 1 as shown in column (2) of Table 4 below.

Due to small sample properties of the PPF-curve and the kinked indifference curves the expansion curve zig-zags around the expansion ray drawn. The optimal choice of each researcher is thus the points closest to this ray. I hope the reader will agree the selection described on Figures 1 and 3 mimics a choice by indifference curves.

2.7 SR4 satisficing is selection of first satisfactory (t_i, b_i)-mixture

Till now it has been assumed that *J* is exogenous. However, researchers may use a stopping rule and stop when a satisfactory model is reached. That is the first point with raypoint exceeding *A* is chosen. If no satisfying point is reached before *J,* use *SR*3.

***SR*4**: Select the first acceptable result where the raypoint exceeds *A*. On Figure 1 eight points are within the IC0. By chance *SR*4 is the one reached first. All these points are larger than 1, and so are the simulated means in column (2) of Table 5 below.

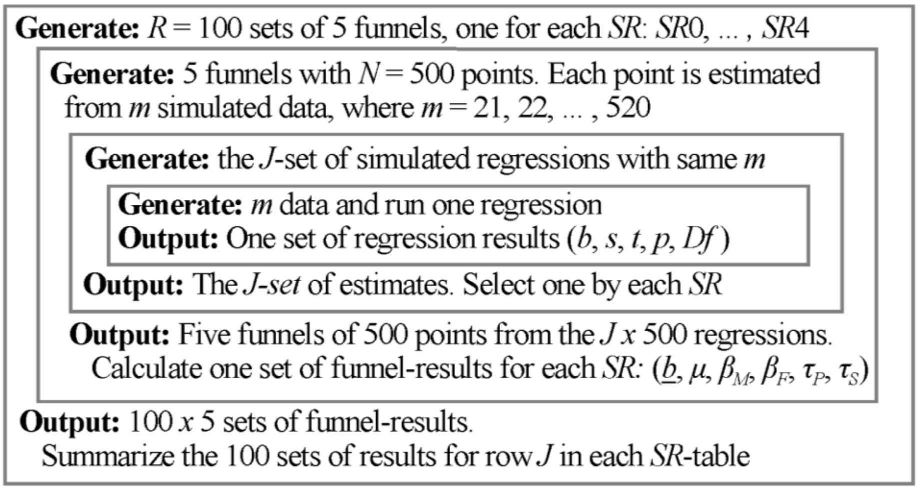
It will be by chance only if *SR*4 reaches the PPF. In the example the probability is 3/8 = 0.375. Note that *J* is endogenous in this *SR*.

3. The simulation setup: running 7 million regressions

The parameter of interest $\beta = \partial y/\partial x$ is the effect of the variable of interest, *x*, on the outcome *y*. In the simulations β is always 1. An estimate of β is termed (*b*, *s*), where *b* is the estimate itself and *s* is its standard error.

Section 3.1 presents the simulation framework and section 3.2 defines the averages and tests used later. The Appendix Table contains a summary of the definitions used in the simulations for easy references.

Figure 4. The experiment for *J* giving one row for each of the 5 *SR*-tables



3.1 *The setup of the simulations – explaining the 'Chinese boxes' of Figure 4*

Each experiment is for one *J*. It gives one row in Tables 1 to 5, which is one table for each *SR*. The five tables have 7 rows for *J* = 1, 5, 10, 15, 25, 34 and 50, which sums to 140:

A *J*-set is *J* regressions, run on simulated data sets with *m* observations. One *funnel point* is a selection by a *SR* from the *J*-set. Thus, the *J*-set provides one point for each of the 5 funnels.

N = 500 is the number of funnel points in each of the five funnels. They are selected by the *SR*s from *J*·500 regressions made. The meta-tests are calculated per funnel.

R = 100 is the number of replications of the funnels used to study the meta-tests.

Behind each funnel with 500 published estimates are thus 500 · 140 = 70,000 estimates, but these estimates are used for five funnels – one for each SR – to make them as comparable as possible. Thus, the average simulated funnel of 500 observations is selected from 70,000 simulated regressions, where 69,500 remain 'hidden'. On average 20 (≈ 140/7) regressions are thus made for each published. Altogether 100 *x* 70'000 = seven million regressions are run.

From each regression the (*b, s, Df*)-set is used. *Df* is the degrees of freedom for the MST. The set allows the *t*-ratio $t = b/s$ and the precision $p = 1/s$ to be calculated. The funnel is the (b, p)-scatter as shown on Figures 4 to 8.

The estimates are done by OLS on the EM (estimation model), from data simulated by the DGP (data generated process). Consequently, the true value for β is one. The DGP/EM pair is made as simple as possible, so that the DGP/EM-pair has no constant.

(7) DGP: $y_t = \beta x_t + \varepsilon_t$, where, $x_t = N(0, \sigma_x^2)$ and $\varepsilon_t = N(0, \sigma_\varepsilon^2)$. The three parameters are $\beta = 1$, $\sigma_x^2 = 2$ and $\sigma_\varepsilon^2 = 10$.

(8) EM: $y_t = b x_t + u_t$, estimated by OLS.

The reason to choose a large value of σ_ε is to get a substantial variation, so that the estimates of β are censored by the main size-prior ($\beta > 0$).

3.2 The format of Tables 1 to 5 reporting the results

Each of the sections about a selection rule brings a couple of typical funnels and one table with simulation results. The funnels are specimens from one row in the table bringing average results for 100 such funnels. The five SR-tables have the same format to make them easy to compare. They have seven rows for the seven values of *J*, and 11 columns reporting the results for statistics used:

Column (1) gives the *J*-value, column (2) reports the mean, $\underline{b}$, and (3) gives the width, μ, (coefficient of variation) of the funnel.

Columns (4) to (7) report the FAT-PET MRA. Column (4) is the PET meta-average, β_M, while column (5) is a count of significant $\beta_M \neq 1$ at the 5 % level of significance, so that the PET does not find the true value. As $R = 100$ it is 'automatically' in %, so at the 5 % level of significance used it should be around 5 if the PET works perfectly well. Column (6) gives the FAT, while column (7) counts of the number of funnels where the FAT rejects symmetry.

Columns (8) and (9) report the average values for the MST, τ_P, and a count of rejection of the MST; i.e., where $\tau_P \neq 1$. Each row in the five tables is for one *J*. The first row is for $J = 1$. All selections give the same result when there is only one estimate to select. Therefore, row 1 is always the same, but then *J* increases and something happens.

4. The results

Sections 4.1 to 4.5 cover the five selection rules one by one. The sections first show a couple of typical funnels generated by the selection rule, and then a table reports a set of seven experiments varying *J*, as explained in section 3.2.

4.1 The ideal selection: SR0

Here the selection is unbiased, and the funnel is symmetric and as lean as predicted by the t-ratios of the estimates (see Callot and Paldam, 2011). The funnels shown have $J = 1$ and 10.

Figure 5. **SR**0: The ideal funnel; see Table 1 rows 1 and 3

Figure 5a. For $J = 1$ — Figure 5b. For $J = 10$

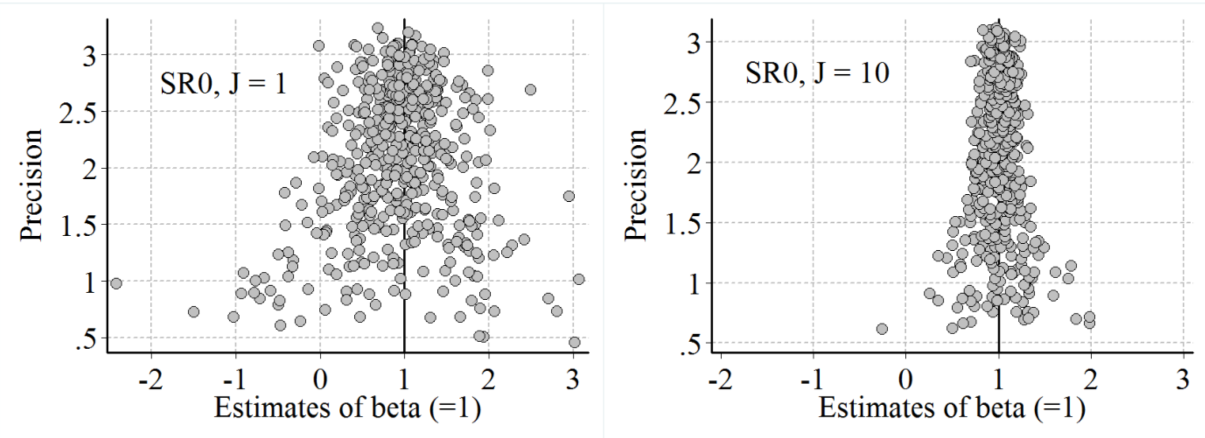


Table 1. Selection rule *SR*0, the ideal selection

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
		Descriptive statistics for		FAT-PET MRA				MST		Bias in % of β	
				PET meta-avr.		FAT, asym.		Test for polishing		Mean	PET
Row	J	$\underline{b}$	μ	β_M	Not 1	β_F	Not 0	τ_P	Not ½	$\underline{b} - \beta$	$\beta_M - \beta$
(1)*	1	0.998	0.411	0.995	5	0.009	5	0.566	56	-0.2	-0.5
(2)	5	1.002	0.183	0.997	4	0.014	4	0.573	98	0.2	-0.3
(3)*	10	1.000	0.128	1.002	5	-0.005	6	0.576	100	0.0	0.2
(4)	15	1.000	0.104	1.001	4	-0.001	4	0.575	100	0.0	0.1
(5)	25	1.000	0.082	1.001	4	-0.001	4	0.574	100	0.0	0.1
(6)	34	1.001	0.070	0.999	1	0.005	1	0.573	100	0.1	-0.1
(7)	50	1.000	0.058	1.000	4	-0.002	3	0.574	100	0.0	0.0
Average results		1.000	-	0.999	3.9	0.003	3.9	-	93.4	0.0	-0.1

Note: * One funnel from rows (1) and (3) is shown on Figure 5. The results for τ_S are worse than (8) and (9).

Table 1b. The fall in μ from column (3) in Table 1 – compared with $\sqrt{J}$

J	Col (3) rel	$\sqrt{J}$	Dif. in %	J	Col (3) rel	$\sqrt{J}$	Dif. in %
1	1	1	0.00	25	0.198	0.224	-0.8
5	0.445	0.447	-0.4	34	0.169	0.172	-1.2
10	0.311	0.316	-1.6	50	0,141	0,141	-0.6
15	0.254	0.258	-1.6				

Note: 'Col (3) rel' is the data in column (3) of Table 1 divided by the estimate for J = 1.

Figure 5a is the same as the selection for J = 1 for all SRs. There is one estimate to choose from so the choice is the same. The figure is rather close to symmetry around 1. Figure 5b shows how quickly the funnel gets leaner when J rises.

Figure 5a is for one funnel. Row (1) of Table 1 reports the average result for 100 such funnels. In the same way Figure 5b is generalized to 100 funnels in row (3) of the Table.

Table 1 shows that both the mean, $\underline{b}$, and the PET, β_M, are very close to 1 as they should be in this case. The bias in columns (10) and (11) is in % of β. The biases are almost the same and always below 1 %. The FAT test is significantly different from 0 in about 5 % of the cases, so these funnels are all symmetric.

In this case there is no polishing as confirmed by the FAT, while the MST finds a lot of polishing. Thus, the FAT tells the right story, while the MST is misleading.

Column (3) shows that the averaging done for $J > 1$ reduces the width of the funnel. Table 1b shows that the reduction is proportional to $\sqrt{J}$ as it should be. Many meta-studies (see Doucouliagos and Stanley (2012)) show that empirical funnels are rather wide. Thus, it is obvious that researchers rarely manage to control their priors. Some do not even try – they are proud to announce that all signs are right in accordance with economic theory!

4.2 The polished funnel: SR1

Now selection rule 1 is applied. For J = 1 the funnel is the same as Figure 5a, but already for J = 5 something happens as shown by Figure 6a, and it becomes clearer on Figure 6b. It is interesting to see that t and b both rise, so that the p's rise marginally only.

(7) $t = b/s = bp$ so that $p = t/b$ becomes the censoring lines that rise with t.

The implication is not very visible on Figure 6a, which looks like Figure 5a with some of the left side censored. Very few negative values appear, and this becomes stronger on Figure 6b.

Figure 6. *SR*1: The polished funnel; see Table 2 rows 2 and 5

Figure 6a. For J = 5

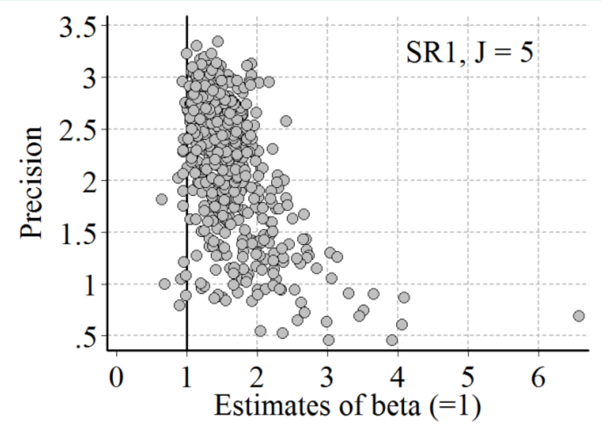


Figure 6b. For J = 25

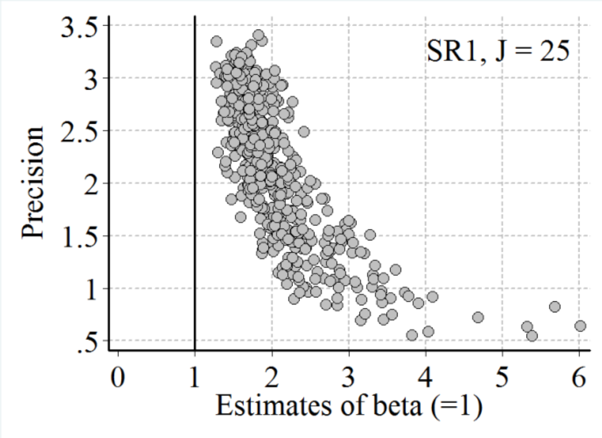


Table 2. Selection rule *SR*1, the polished funnel

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
		Descriptive statistics for		FAT-PET MRA				MST		Bias in % of β	
				PET meta-avr.		FAT, asym.		Test for polishing		Mean	PET
Row	J	$\underline{b}$	μ	β_M	Not 1	β_F	Not 0	τ_P	Not ½	$\underline{b}-\beta$	$\beta_M-\beta$
(1)	1	0.998	0.411	0.995	5	0.009	5	0.566	56	-0.2	-0.5
(2)*	5	1.419	0.242	0.978	5	1.229	100	0.332	100	41.9	-2.2
(3)	10	1.544	0.230	0.975	12	1.603	100	0.295	100	54.4	-2.5
(4)	15	1.610	0.229	0.964	29	1.833	100	0.276	100	61.0	-3.6
(5)*	25	1.687	0.228	0.960	39	2.075	100	0.258	100	68.7	-4.0
(6)	34	1.729	0.229	0.952	48	2.234	100	0.247	100	72.9	-4.8
(7)	50	1.780	0.231	0.956	46	2.377	100	0.239	100	78.0	-4.4
Average results		1.538	-	0.968	26.3	-	86.4	-	93.7	53.8	-3.2

Note: * One funnel from rows (2) and (5) is shown on Figure 6. The results for τ_S are worse than (8) and (9).

With the form of the funnel shown it is no wonder that the mean becomes more and more biased as J rises. And the FAT certainly shows that the funnel is asymmetric. Polishing is not, strictly speaking, a censoring, but still the PET works rather well. Even if the PET ≠ 1 in half the cases for high Js it is still within 5 percentage points from 1, and much better than the mean. Note that the bias of the mean is always positive.

It is interesting to look at column (3). While the funnel width was falling rather strongly with J for *SR*0, it falls in the beginning for *SR*1 and then it stabilizes. This will be the typical result for *SR*2, 3 and 4 as well.

The MST detects polishing in all the cases, where there is polishing, but also in half of the cases for J = 1 where there is none. The FAT gives the right answer throughout.

4.3 *The censored funnel: SR2*

Now the funnel is generated by *SR*2, which selects the largest value in the *J*-set. The two parts of Figure 7 look much like their counterparts on Figure 6.

Figure 7. *SR*2: The censored funnel; see Table 3 rows 2 and 5

Figure 7a. For $J = 5$ Figure 7b. For $J = 25$

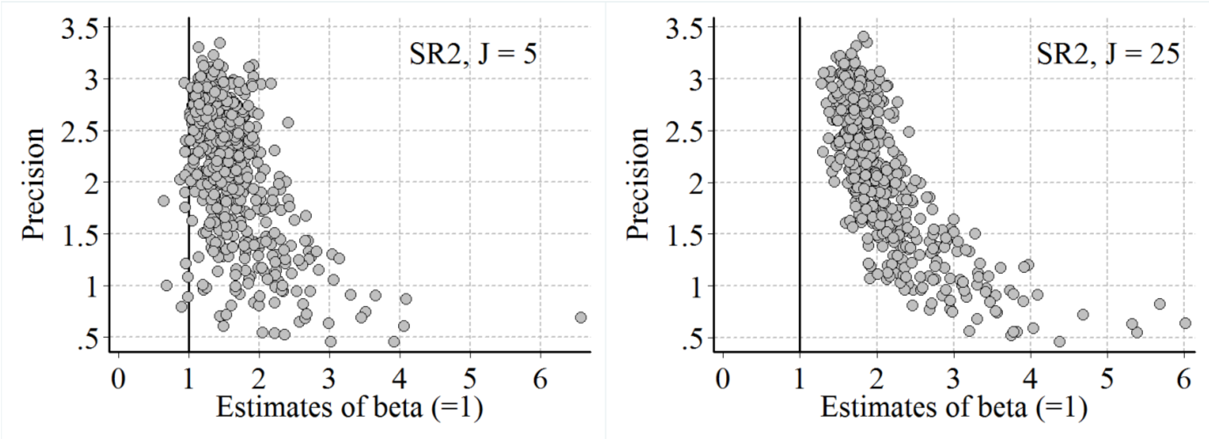


Table 3. Selection rule *SR*2, the censored selection

Row	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
		Descriptive statistics for		FAT-PET MRA				MST		Bias in % of β	
				PET meta-avr.		FAT, asym.		Test for polishing		Mean	PET
	J	$\underline{b}$	μ	β_M	Not 1	β_F	Not 0	τ_P	Not ½	$\underline{b} - \beta$	$\beta_M - \beta$
(1)	1	0.998	0.411	0.995	5	0.009	5	0.566	56	-0.2	-0.5
(2)*	5	1.433	0.241	1.004	1	1.165	100	0.341	100	43.3	0.4
(3)	10	1.570	0.231	1.014	10	1.499	100	0.310	100	57.0	1.4
(4)	15	1.643	0.233	1.012	5	1.703	100	0.293	100	64.3	1.2
(5)*	25	1.729	0.236	1.020	12	1.904	100	0.281	100	72.9	2.0
(6)	34	1.778	0.239	1.019	10	2.036	100	0.272	100	77.8	1.9
(7)	50	1.836	0.244	1.030	25	2.155	100	0.267	100	83.6	3.0
Average results		1.570	-	1.013	9.7	-	86.4	-	93.7	57.0	1.3

Note: * One funnel from rows (2) and (5) is shown on Figure 7. The results for τ_S are worse than (8) and (9).

This selection rule is solved analytically as done in Paldam (2013a), and the results tally. It is also easy to see that the figures for $J = 5$ are more similar for *SR*1 and *SR*2 than for $J = 25$. Table 3 shows that this is a general result: The mean rises a little more for *J* rising with *SR*2 than with *SR*1. In fact, the bias of the mean is quite large for *SR*2, where it reaches 100 % (so that the mean is 2) for $J \approx 70$.

This is the case T.D. Stanley had in mind when he developed the FAT-PET, and the PET works amazingly well finding the true value. The results for the FAT and the MST are the same as before.

4.4 The combined selection: SR3

As the combined *SR*3 is a mixture of *SR*1 and *SR*2 and they look alike, it is no wonder that Figure 8 looks much like Figures 6 and 7. However, Table 4 shows a few interesting features.

Basically the results are even better than for *SR*1 and *SR*2. The PET count is higher than in the two previous tables and the PET bias is smaller. Here the average ratio between the $PB/PB_{PET} \approx 50$, so the gain from using the PET is high.

Figure 8. SR3: The combined funnel, see Table 4 rows 2 and 5

Figure 8a. For J = 5 Figure 8b. For J = 25

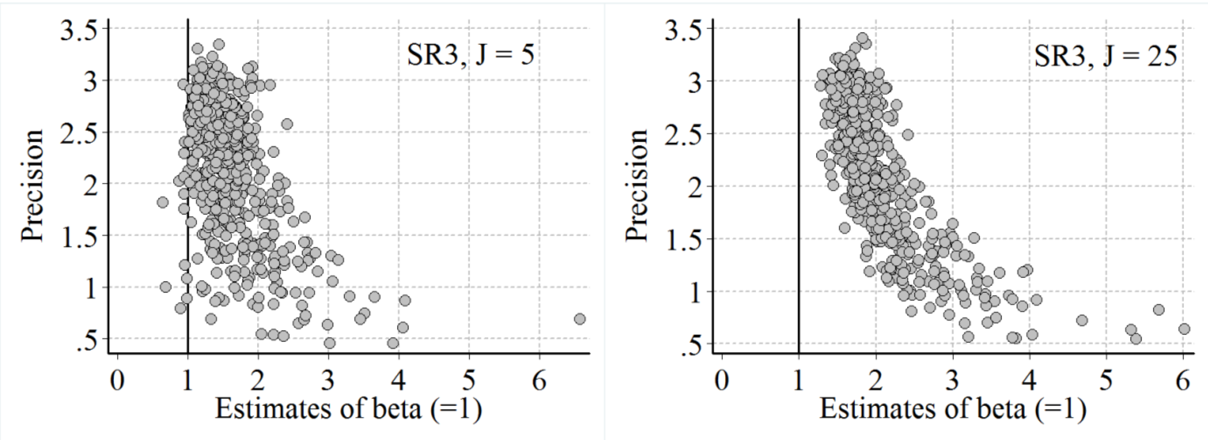


Table 4. Selection rule *SR*3, the combined selection

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
		Descriptive statistics for		FAT-PET MRA				MST		Bias in % of β	
				PET meta-avr.		FAT, asym.		Test for polishing		Mean	PET
Row	J	$\underline{b}$	μ	β_M	Not 1	β_F	Not 0	τ_P	Not ½	$\underline{b}-\beta$	$\beta_M-\beta$
(1)	1	0.998	0.411	0.995	5	0.009	5	0.566	56	-0.2	-0.5
(2)*	5	1.429	0.241	0.990	1	1.206	100	0.335	100	42.9	-1.0
(3)	10	1.562	0.230	0.993	6	1.567	100	0.300	100	56.2	-0.7
(4)	15	1.633	0.231	0.987	7	1.786	100	0.281	100	63.3	-1.3
(5)*	25	1.716	0.232	0.988	3	2.014	100	0.266	100	71.6	-1.2
(6)	34	1.763	0.235	0.983	10	2.163	100	0.256	100	76.3	-1.7
(7)	50	1.819	0.238	0.989	7	2.298	100	0.249	100	81.9	-1.1
Average results		1.560		0.989	5.6	-	86.4		93.7	56,0	-1.1

Note: * One funnel from rows (2) and (5) is shown on Figure 8. The results for τ_S are worse than (8) and (9).

The results from the FAT and MST are as before. They both find biased when it is actually biased, but the MST also finds it when it is not.

The results till now suggest that it does not make a big difference if the selection rule is *SR*1, *SR*2 or *SR*3. It follows that the results are rather robust to any mixture of the three selections.

4.5 The satisficing choice: SR4

The results of applying *SR*4 are much as the three previous *SR*s for small *J*s, as expected, but as *J* rises more choices differ as this *SR* may stop selecting well before it reaches *J*. This is obvious when Figure 9b is compared to the three previous b-figures.

Figure 9. *SR*4: The satisficing funnel, see Table 5 rows 2 and 5

Figure 9a. For $J \leq 5$

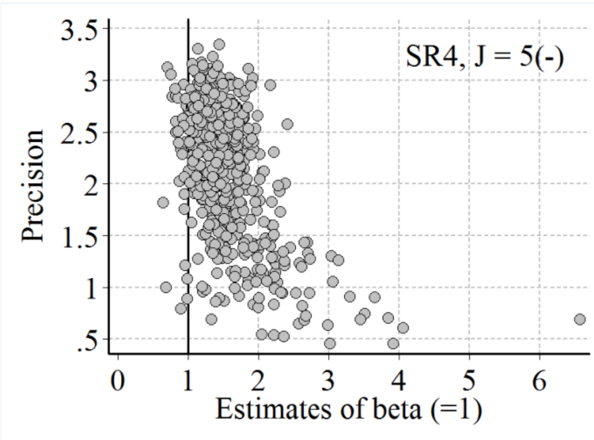


Figure 9b. For $J \leq 25$

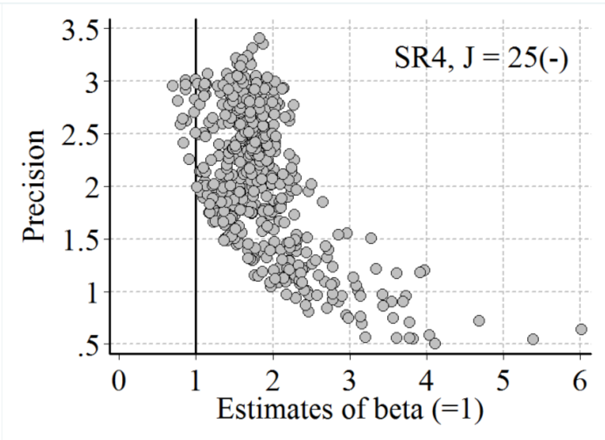


Table 5. *SR*4: The satisficing *SR*, select the first acceptable result

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
		Descriptive statistics for		FAT-PET MRA				MST		Bias in % of β	
				PET meta-avr.		FAT, asym.		Test for polishing		Mean	PET
Row	J	$\underline{b}$	μ	β_M	Not 1	β_F	Not 0	τ_P	Not ½	$\underline{b}-\beta$	$\beta_M-\beta$
(1)	1	0.998	0.411	0.995	5	0.009	5	0.566	56	-0.2	-0.5
(2)*	5	1.342	0.277	0.853	98	0.135	100	0.302	100	34.2	-14.7
(3)	10	1.429	0.280	0.841	98	1.623	100	0.273	100	42.9	-15.9
(4)	15	1.470	0.284	0.845	99	1.735	100	0.265	100	47.0	-15.5
(5)*	25	1.520	0.290	0.855	91	1.849	100	0.261	100	52.0	-14.5
(6)	34	1.545	0.293	0.858	85	1.915	100	0.261	100	54.5	-14.2
(7)	50	1.577	0.298	0.867	80	1.981	100	0.260	100	57.7	-13.3
Average results		1.412	-	0.873	79.4	-	86.4	-	93.7	41.2	-12.7

Note: (2)* is the statistics for Figure 9a, and (5)* is shown on Figure 9b. Columns (8) and (9) will be revised.

This also means that the publication bias increases less when J rises as seen in column (2) of Table 5. The PET is still adjusting the average, so that it gets closer to 1 than the mean, but it is not as efficient as for the three previous SRs.

4.6 Varying the parameters and missing aspects

The setup of the analysis contains few parameters the can be varied: J, SR, β, m, σ_x and σ_ε. The experiments reported cover SR and J. I take the m-set to be a realistic range. If β is changed, all that happens is a linear shift along the horizontal axis.

Thus, only the two standard deviations σ_x and σ_ε remain. They have been submitted to a set of experiments using 1 funnel for each SR. The results are rather robust to changes in σ_x as long as σ_ε is larger. Changes in σ_ε appear as a contraction/expansion of the horizontal axis.

The paper has run through a set of experiments using a certain setup for the simulations. Within this setup the results are rather robust. However, the setup is restrictive in some respects. The most important restriction is that the experiments deal with data-variation not model variation. This may be one reason why the results for SR1 to SR4 are fairly similar, and it also suggests that the main reason for the excess width of empirical funnels is model variation rather than data variation.

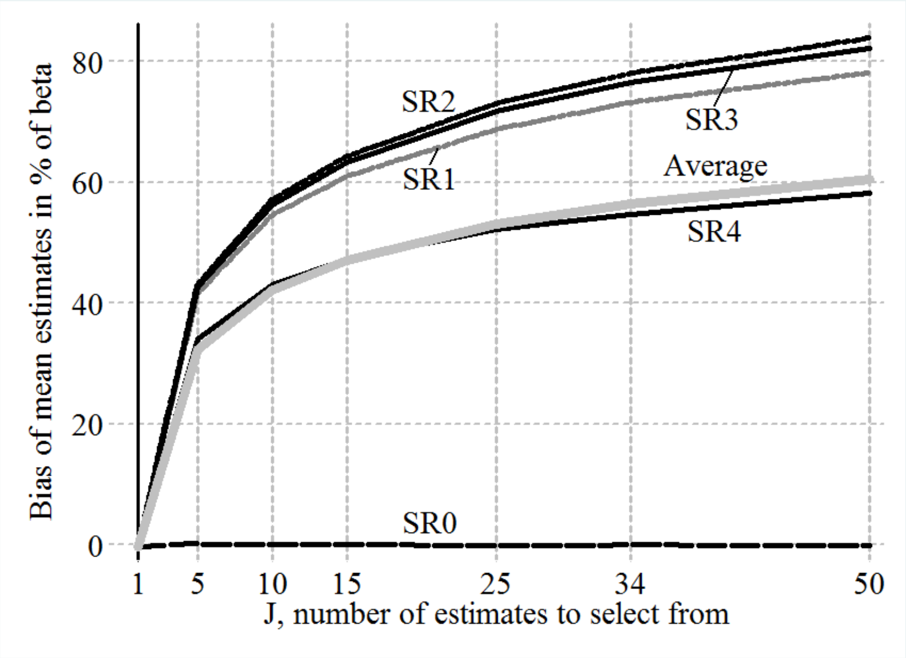
5. The pattern in the results

Each of the tables 1 to 5 reports a set of experiments with one selection rule. They are compared across rules in this section. First, section 5.1 compares the publication bias, and then section 5.2 compares the bias in the PET. Section 5.3 looks at, μ, the coefficient of variation. Section 5.4 compares the FAT and the MST.

5.1 The publication bias, columns (10) from the five tables

The five tables give rather clear results for the publication bias ($\underline{b} - \beta$) = ($\underline{b}$ – 1). They are shown in Figure 10. The true value β = 1 is a horizontal line at zero. The *SR*0-line is close to this, but the other 4 lines are all higher, showing biases which are always upwards and substantial.

Figure 10. The paths of the publication bias for the mean



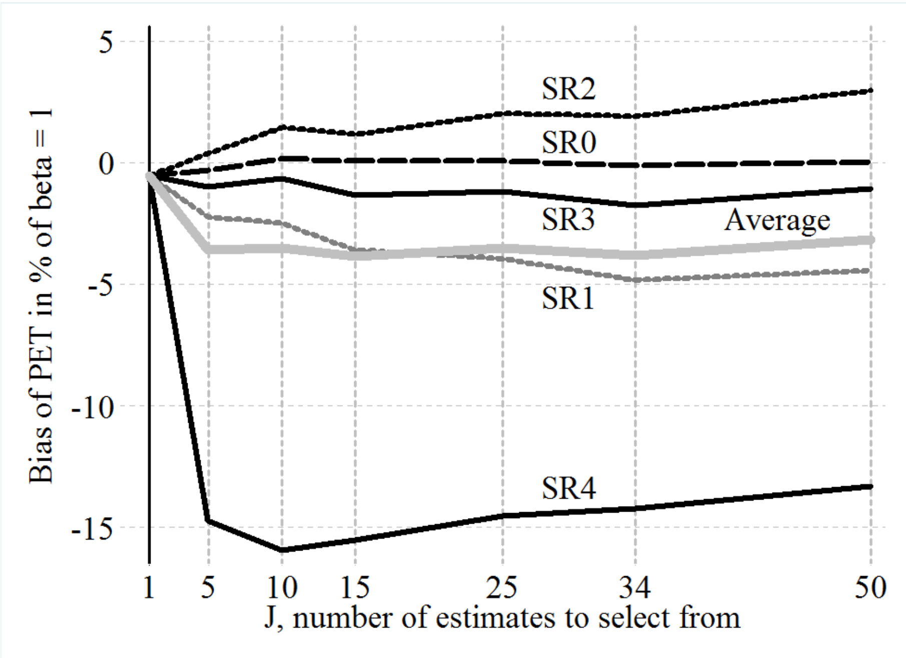
From interviews and introspection I believe that the researchers in a typical literature in economics use some mixture of the five selection rules – and perhaps a few more. Often it is even mixed in the same paper, and many researchers find it difficult to fully explain the choices made. It may be overly brave, but perhaps we can take an average of the five *SR*s as a realistic guess of the publication bias. If *J* is between 20 and 30, the average publication bias is thus just a bit above 50 %. From the 500 meta-studies made so far in economics this appears a little on the low side.

The introduction made the assumption that economic theory predicted that $\beta > 0$, and β was accordingly chosen at 1. This gave a bias so that the average result was well above 1. Thus, the simulations produced a bias-exaggeration result. Theory is self-confirming.

5.2 The bias of the PET, columns (11) from the five tables

Columns (11) of the 5 tables of results show that the PET meta-average is normally much closer to β than is the mean, even in the case of *SR*4. But it is rarely a perfect estimate of β. Note that Figure 11 uses a much enlarged vertical axis compared to Figure 10.

Figure 11. The paths of the bias of the PET



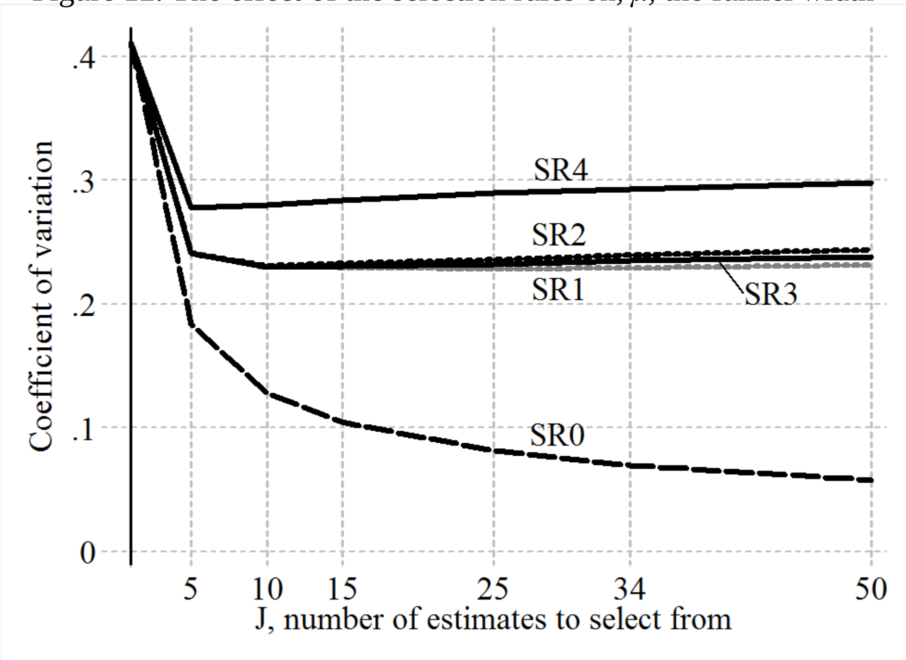
*SR*0 has no selection bias, and there the curve is horizontal at zero as it should. In the cases *SR*1-3 the PET bias is still rather close to zero. For SR4 the PET bias is about 15 %. Still, the average result is within 5 % of the true value for all *J*s examined. The bias of the PET is less than one tenth of the bias of the mean.

From prior studies (Stanley 2008 and Paldam 2013b) it is known that the PET works perfectly well if the lowest half of the points in the funnel is censored. Thus, the PET does a good job in a range of seemingly realistic circumstances.

5.3 *The coefficient of variation, μ, columns (3) from the 5 tables*

One of the most puzzling observations from meta-studies is the amazing widths of funnels. It has been analyzed by the variable μ, in the tables. Figure 12 shows the μ-lines for all the *SR*s like in Figure 10. All curves start at the same point 0.411 for $J = 1$ and then they fall, but only the *SR*0-curve keeps falling. The lines are somewhat different. For *SR*0 the line falls with rising *J*'s with the square root of *J*, very much as expected.

Figure 12. The effect of the selection rules on, μ, the funnel width



The other four *SR*s all cause μ to fall a little – and then they start to rise. This contrasts somewhat to the observed excessive width of funnels in the typical meta-study.

5.4 *The FAT and the MST, columns (6) and (8) from the five tables*

The FAT is known as a very robust test. Figure 13 compare the results from the five tables. It should reject asymmetry for $J = 1$ and all estimates using SR0, and detect asymmetry in all other cases. This is precisely what it does. It is interesting that the results are rather similar for all four optimizing SRs, and that the highest test-values are for SR1.

The MST gives two tests of the same and no estimate of the meta-average. It can be run for either H0: $\tau_S = 0$ or $\tau_P = ½$. The most reasonable picture is for τ_P. Figure 14 compares the results. As usual SR0 is unbiased, while the other 4 SRs are biased for $J > 1$.

Figure 13. The FAT

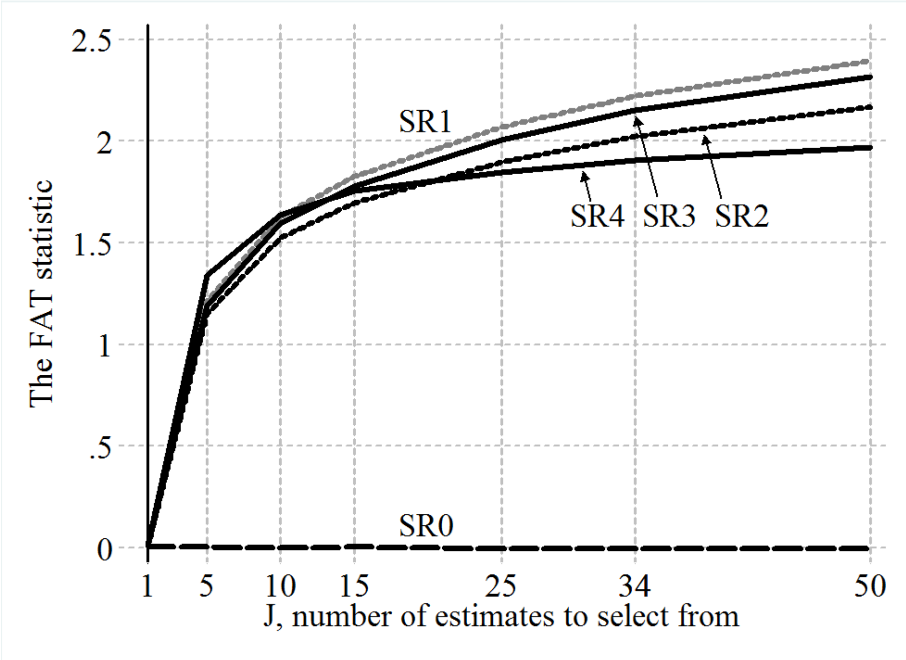
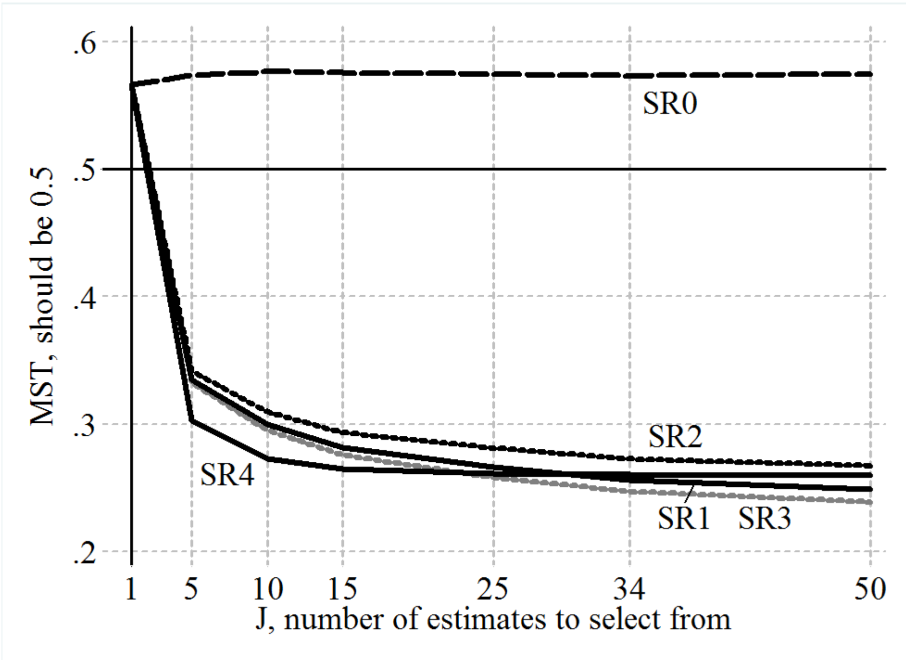


Figure 14. The MST. Is τ_P = ½?



The MST gives results that are even closer than the FAT for the four biased *SR*s. In addition a number of cases have occurred where the MST detected bias when there was none. The FAT did not do that.

The conclusion is that the FAT is a better test, and in general the FAT-PET encompasses the MST. This is the same conclusion as in Stanley and Doucouliagos (2012).

6. Conclusions

Most researchers make more regressions than they publish. This situation is simulated by assuming that authors run J regressions to select the estimate published. The paper studies a set of 5 selection rules, SR, which often seems to be used by authors. The simulations model cases where all $N = 500$ estimates in the β-literature use the same J and the same SR-rule. In practice studies vary in (at least) three different ways:

(V1) Authors have different selection rules.

(V2) J differs between authors.

(V3) Most of the variation between the estimates is probably due to model variation.

(V1) is analyzed by showing that the results are robust to different averages of the 5 selection rules. (V2) is analyzed by considering a broad range of Js.

(V3) is more difficult to handle. I have tried to do this by increasing the data variation, but the simulated funnels are not as wide as empirical funnels. One of the five selection rules is the ideal one SR0, with no publication bias. It causes funnels to be very narrow, so it must be rare in practice. Thus, the analysis catches some of the problems of the publication game, but underestimates other problems.

The simulations find a publication bias that is almost as large as the typical empirical one. One particularly troublesome finding is that all biases found are in the direction of the prior generating the bias. Thus, empirical research has a bias towards the confirmation of economic theory.

The good news is that the bias of the mean is insensitive to the combination of the other four optimal selection rules, and the PET is a rather fine tool finding the true value of β. It is not, of course, perfect, but it always has a much smaller bias than the mean.

References:[7]

Callot, L., Paldam, M., 2011. Natural funnel asymmetries. A simulation analysis of the three basic tools of meta-analysis. *Research Synthesis Methods* 2, 84–102

Card, D., Krueger, A.B., 1995. Time-series minimum-wage studies: a meta-analysis. *American Economic Review* 85, 238-43

Doucouliagos, H., Paldam, M., 2008. Aid effectiveness on growth. A meta study. *European Journal of Political Economy* 24, 1-24

Doucouliagos, H., Paldam, M., 2011. The ineffectiveness of development aid on growth: An update. *European Journal of Political Economy* 27, 399–404

Doucouliagos, H., Paldam, M., 2013. The robust result in meta-analysis of aid effectiveness: A response to Mekasha and Tarp. *Journal of Development Studies* 49 (4), 584–87

Doucouliagos, H., Stanley, T.D., 2012. Are All Economic Facts Greatly Exaggerated? Theory Competition and Selectivity. *Journal of Economic Surveys* 27, 316-39

Egger, M., Smith, G. D., Schneider, M., Minder, C., 1997. Bias in meta-analysis detected by a simple, graphical test, *British Medical Journal* 316, 629-34

McCloskey, D.N., 2nd ed., 1998. *The Rhetoric of Economics*. University of Wisconsin Press, Madison

Paldam, M., 2013a. Regression Costs Fall, Mining Ratio Rise, Publication Bias Looms, and Techniques get Fancier. Reflections on some trends in Empirical Macroeconomics. *Econ Journal Watch* 10, 136-56

Paldam, M., 2013b. How do partly omitted control variables influence the averages used in meta-analysis in economics? Economics Working Papers, Aarhus University 2013-22

Stanley, T.D., 2008. Meta-regression methods for detecting and estimating empirical effect in the presence of publication bias. *Oxford Bulletin of Economics and Statistics* 70, 103-27

Stanley, T.D., Doucouliagos, H., 2012. *Meta-Regression Analysis in Economics and Business*. Routledge, Abingdon (UK)

Stanley, T.D., Doucouliagos, H., Giles, M., Heckmeyer, J.H., Johnson, R.J., Laroche, P., Nelson, J.P, Paldam, M., Poot, J., Pugh, G., Rosenberger, R.S., Rost, K., 2013. Reporting Guidelines for Meta-Regression Analysis in Economics. *Journal of Economic Surveys* 27, 390-4

Ziliak, S.T., McCloskey, D.N., 2008. *The Cult of Statistical Significance: How the Standard Error Costs Us Jobs, Justice, and Lives*. University of Michigan Press, Ann Arbor

7. The home page of the project of the author has the URL: http://www.martin.paldam.dk/Meta-Method.php.

Appendix 1. Definitions and numbers used to generate the 5 SR-tables: Table 1 to 5

One experiment: Row *J* in the 5 SR-tables. The numbers *R, N, J* and 5

The 5 SR-tables (1 to 5) each report the analysis of one selection rule, SR0, …, SR4

J = 1, 5, 10, 15, 25, 34 and 50, with Σ = 140. Each J gives one line in each SR table

J is the size of the J-set. One J-set is estimated on J data sets, with the same m

The same J-set is used for all 5 SRs that each gives one point for each of five funnels.

N = 500 is the number of points in each funnel, reached by varying m from 21, 22, … , 520

Each funnel is analyzed by a meta-analysis giving the meta-results ($\underline{b}$, μ, β_M, $C\beta_M$, β_F, $C\beta_F$, τ_P, $C\tau$, PB, PB_{PET})

Where $C\beta_M$, $C\beta_F$ and $C\tau_P$ is 1 if β_M, β_F or $\tau_P \neq 0$, else 0

Each of the 5 funnels is replicated R = 100 times to study the robustness of the meta-results, which are

summarized as ($\underline{b}$, $\underline{\mu}$, $\underline{\beta_M}$, $\Sigma C\beta_M$, $\underline{\beta_F}$, $\Sigma C\beta_F$, $\underline{\tau_P}$, $\Sigma C\tau$, $\underline{PB}$, $\underline{PB_{PET}}$) , where the underlining indicate a mean

The total number of regressions made is: $R\ N\ \Sigma J = 100 \cdot 50 \cdot 141 = 7{,}050{,}000$

The simulation framework: The DGP/EM-pair for a given *m*

data	$x_t = N(0, \sigma_x^2)$, where $\sigma_x^2 = 2$	$\varepsilon_t = N(0, \sigma_\varepsilon^2)$, where $\sigma_\varepsilon^2 = 10$
DGP	data generating process: $y_t = \beta\, x_t + \varepsilon_t$	$\beta = 1$ is the parameter of interest
EM	estimating model: $y_t = b\, x_t + u_t$,	Estimated by OLS

The five selection rules used on each *J*-set

SR0	Unbiased, select averages $\underline{b}_j$ and $\underline{t}_j$ over J	See Table 1 in section 2.2, J is fixed
SR1	Polishing, best fit, select b_j with largest t_j	See Table 2 in section 2.3, J is fixed
SR2	Censoring, best size, select largest b_j	See Table 3 in section 2.4, J is fixed
SR3	Best (b_j, t_j)-combination	See Table 4 in section 2.6, J is fixed
SR4	First satisfactory (b_j, t_j) selected	See Table 5 in section 2.7, $j \leq J$

The *B*-set of *N* = 500 estimates b_i for one funnel

(b_i, s_i)	The estimate and its standard error	B-set, the N estimates, i = 1, …, N
t_i, p_i	t-ratio and precision calculated from (b_i, s_i)	$t_i = b_i/s_i$ and pi = 1/si
funnel	(p_i, b_i)- scatter. Show distribution of B-set	Broad for small p's, narrows for p growing
$\underline{b}$, *Std*	mean (arithmetic) and standard deviation of	Calculated over N
$\mu = Std/\underline{b}$	Coefficient of variation	Measure for width of funnel

The tests analyzed: Two MRAs, meta-regression analysis

FAT-PET	Estimate of the PET meta-average that detects and adjusts for censoring	
Equation	$b_i = \beta_M + \beta_F\, s_i + u_i$ or after division with s_i	$t_i = \beta_M\, p_i + \beta_F + v_i$ estimated with OLS
β_M	PET, Precision Estimate Test	Test: H0: $\beta_M = 0$
β_F	FAT, Funnel Asymmetry Test	Test: H0: $\beta_F = 0$. Iff $\beta_F \neq 0$ then $\beta_M \neq \underline{b}$
MST	Meta Significance Test that indicates polishing	
Equation	$\text{Ln}\, \lvert t_i \rvert = \tau_S + \tau_P \ln df_i + u_i$	Polishing test: H0: $\tau_P = 0$

The bias analyzed

Main prior	Widespread so it significantly affect mean	It is assumed to be the right sign: $\beta > 0$
$SB_i = b_i - \beta$	Selection bias, SB_i-set. PB is mean of SB_i-set	Main priors leads to exaggeration of results
$PB = \underline{b} - \beta$	Publication bias, $\underline{b}$ is the mean of B-set	Due to biased selections at the hidden level
$PB_{PET} = \beta_M$	Bias of PET estimate	We expect that $PB_{PET} < BP$

Economics Working Papers

2013-14: Peter Arendorf Bache and Anders Laugesen: Trade Liberalisation and Vertical Integration

2013-15: Kaleb Girma Abreha, Valérie Smeets and Frédéric Warzynski: Coping with the Crisis: Recent Evolution in Danish Firms' - International Trade Involvement, 2000-2010

2013-16: Peter Arendorf Bache and Anders Laugesen: An Industry-Equilibrium Analysis of the LeChatelier Principle

2013-17: Anna Piil Damm and Christian Dustmann: Does Growing Up in a High Crime Neighborhood Affect Youth Criminal Behavior?

2013-18: Christian Bjørnskov and Jacob Mchangama: Do Social Rights Affect Social Outcomes?

2013-19: Benoit Julien, John Kennes, and Moritz Ritter: Bidding for Clubs

2013-20: Ina Charlotte Jäkel: Import-push or Export-pull?

2013-21: Tor Eriksson, Jay Pan and Xuezheng Qin : The Intergenerational Inequality of Health in China

2013-22: Martin Paldam: How do partly omitted control variables influence the averages used in meta-analysis in economics?

2013-23: Ritwik Banerjee: An Evaluation of the Revenue side as a source of fiscal consolidation in high debt economies

2013-24: Nabanita Datta Gupta, Mona Larsen and Lars Brink Thomsen: Do wage subsidies for disabled workers result in deadweight loss? – evidence from the Danish Flexjob scheme

2013-25: Valerie Smeets, Sharon Traiberman and Frederic Warzynski: Offshoring and Patterns of Quality Growth: Evidence from Danish Apparel

2013-26: Torben M. Andersen, Jonas Maibom, Michael Svarer and Allan Sørensen: Do Business Cycles Have Long-Term Impact for Particular Cohorts?

2013-27: Martin Paldam: Simulating publication bias