Online Appendix

Table OA1: Project performance of MDBs – literature review.

Scholar(s)	Topic & Sample	Contribution	Variables	Selection bias addressed
Bulman et al. (2015)	Macro and micro correlates of project performance; sample: World Bank projects (n=3821, since 1995) and Asian Development Bank (n=1342, since 1973) projects	Provided an innovative insight into under investigated relative importance of country versus project characteristics in driving aid effectiveness; comparison the correlates of project success in Asian Development Bank with World Bank; studied similarities and differences across institutions in the relationship between project outcomes and country and project characteristics.	Project outcome (DV) based on project's development outcome; Country Policy and Institutional Assessment ratings; Real GDP per capita growth; Freedom House rating; Dummy for PAR/PPER evaluations; Dummy for ADB PVR evaluations; size log (total commitment); Planned project length; Effectiveness delay; Implementation day; Additional funding; Project manager track record; Project manager turnover; Negative rating in first half ('warning rating').	No (Did not addressed it econometrically. Only mentioned that their results should be interpreted with some caution because of the influence of unobservable project characteristics on project selection)
Dollar and Levin (2005)	Institutional quality and project outcomes; Sample: World Bank development projects; 1990-1999.	Introduced macroeconomic evidence on factors conducive to the success of aid-funded projects in developing countries.	Project success rate (DV); Log of GDP/capita; Rule of law index; Freedom House index; single index of institutional quality from Kaufman, Kraay, and Zoido-Lobaton (1999); Aid/GDP; the percent of the country's territory situated in the tropics; country (not included in the regs), region (included in the regs).	No (Found little evidence that selection bias problems were impacting the conclusions, so took no action)
Guillaumont and Laajaj (2006)	Effects of economic instability on projects success; sample: World Bank development projects; n=2,894; 1981-2002	Showed that the previous macroeconomic studies arguing that aid effectiveness is higher in vulnerable countries because it dampens the negative effects of shocks is inconsistent with the observation that the success of the projects is lower in an unstable environment.	Project outcome rating (DV); Index of economic instability (export variability); Official Development Assistance as a share of GNI; country log of the rate of exports during the project; initial level of education and quality of institutions; sector of the project, a dummy for IDA/IBRD, a dummy for Investment/Adjustment loans; country being oil exporter; political instability	Yes (addressed it by using instruments (IV) based on the characteristics of the donors)

Scholar(s)	Topic & Sample	Contribution	Variables	Selection bias addressed
Kilby (2012)	Effects of donor agencies on project outcomes; sample: World Bank development projects; n=4691; approval dates 1986-2008	used a stochastic frontier model to generate a measure of World Bank project preparation duration based on a variation in political economy factors that are exogenous to latent project quality.	Outcome (IEG overall project performance rating); project preparation time; total project cost; IDA funds dummy variable; Structural Adjustment Loan dummy; Dummy indicating major conflict; population; PPP GDP per capita; Democracy dummy; Averaged Freedom House Rating; Alignment with US on UN votes important to US; Alignment with other G7 on other UN votes; Alignment with G7-1 important votes; Alignment with G7-1 other votes; Dummy for US military aid>0.5; Log of disbursements of US economic aid; Log average disbursements Like-minded donor aid; Indicator for country holding non-permanent UNSC seat; Country held World Bank ED seat in current year or past 3 years.	No (Excluded the projects which were cancelled before the implementation (e.g. the borrower never signed the project loan docs) and claimed that the sample selection bias does not appear to be an issue)
Denizer et al. (2013)	Macro and micro correlates of project performance; sample: World Bank development projects; n=6,000; 1983-2011	Found that the success of individual development projects varies much more WITHIN countries than it does BETWEEN countries. Applied their findings to potential implications for donor policies aimed at aid effectiveness.	World Bank IEG outcome rating; PPAR review; IEG Desk review; Real GDP per capita growth; CPIA score; Freedom House; Dummy for investment project; Fraction of project in largest sector; 'Repeater' projects; Original project commitment; Time b/t approval and completion; Preparation cost/commitment; Supervision costs/commitment; Time from approval to first disbursement; Project restructured in first half; Problem project flag in first half; Potential problem project flag in first half; Temporary membership	No (Did not directly addressed it. Mentioned that due to the feasibility of the data on the project characteristics (e.g. unobserved project quality) not possible to find some plausibly-exogenous source of project-quality in order to reduce the scope of selection bias)

Scholar(s)	Topic & Sample	Contribution	Variables	Selection bias addressed
			on the UNSC; Membership on WB Executive Board; lag between the end of implementation and evaluation & dummy for ratings based on audits; Task team leader quality; Task team leader's turnover.	
Chauvet et al. (2015)	Supervision and project performance; sample: World Bank projects; n=2,000; 102 countries	By using extended principal-agent theory, they found, consistent with the existing theory, that donor supervision of projects was significantly more effective in improving project performance where interests were widely divergent.	Success of the project (DV); Preparation time; Supervision; IDA dummy; lending instruments; duration of the project; Log of initial GDP per capita (in constant dollars); time leader in office; CPIA indices; LICUS countries; Co-financing dummy; NGO dummy; capacity dummy; Same language as donor; same religion as donor; distance from capitals; Total aid budget of donor.	Yes (used IV approach. Specifically, instruments which are uncorrelated with project performance but correlated with supervision and preparation. Also, used instruments for supply-side determinants of the amounts of aid received. Instruments for supervision and preparation: characteristics of the projects (co-financing dummy, NGO dummy, knowledge capacity building dummy); distance and supply-side variables (same language as donor, same religion as donor, distance from capitals, total aid budget of donor).
Geli et al. (2014)	Project characteristics and project outcome ratings; sample: World Bank projects; n=2,729;	Explored the in-sample and out-of-sample predictive performance of empirical models relating project outcomes to project characteristics observed in the life of a project.	Outcome ratings ISR-DO ratings; Project size; Preparation time; Elapsed time b/t approval and effectiveness; Initially planned project length; TTL track record; Country policy performance.	No

Scholar(s)	Topic & Sample	Contribution	Variables	Selection bias addressed
	1995-2012			
Isham et al (1997)	Civil liberties, democracy and the project performance; sample: World Bank projects	Used cross-national data set on the performance of government investment projects financed by the World Bank to expatriate the link between government efficacy and governance. Demonstrated a strong empirical link b/t civil liberties and the performance of government projects. The strong effect of civil liberties holds true even when controlling for the level of democracy.	Economic rate of return; Freedom House; various civil unrest indicators; Project complexity; Terms of trade shock; Black market premia; Fiscal surplus; GDP growth; Regional dummy; Sectoral dummy; Capital-labour ratio.	No
Dollar and Svensson (2000)	Factors driving the project performance of structural adjustment programmes; sample: World Bank projects, n=220	Used new database on 220 reform programmes to analyse the causes of success or failure of adjustment programmes. Found that this depends on domestic political-economy forces.	Reform outcome (0-1 dummy reflecting failure or success of each reform programme as determined by OED of World Bank); Ethnic fractionalisation; Political instability; Democratically elected; Time in power; Preparation staff weeks; Supervision staff weeks; Finance conditions; Macro & fiscal conditions; Sectoral conditions; Trade conditions; No. of conditions in loan agreement; Loan size; Expected reform period; Prior analytical work; Region; Initial GDP per capita; Initial population.	Yes (used instruments in two-stage procedure to estimate probit regression model (i.e. exogenous variables that are correlated with the Bank's effort but that do not influence success or failure of reforms)
Kilby (2000)	Project supervision and performance; sample: World Bank projects; n=1426; 1981-1991	Explored the impact of donor supervision on World Bank development project performance. Used maximum likelihood estimation of a restricted ordered	Project success rating provided by WB IEG; No. of staff weeks of World Bank supervision; Region; Sectors; Loan amount; Supervision level; No. of staff weeks preparation; Growth of GDP per	No

Scholar(s)	Topic & Sample	Contribution	Variables	Selection bias addressed
		probit function.	capita; Change in Index of Openness. Note: Loan amount was deflated using a US GDP deflator for middle year of the project i.e. the board approval date plus 1 year for 2-year periods, 2 years for 3- and 4-year projects and 3 years for longer projects	
Pohl & Mihaljek (1992)	Project evaluation and uncertainty; sample: World Bank projects; n=1,015; 1974-87 (i.e. by date when the project completion report was issued)	Concluded that the project analysis suffers from a large degree of uncertainty which the traditional methods of project evaluation and selection have not been able to reduce.	Economic rate of return; Total project cost; Nominal cost overrun; Unexpected inflation; Time overrun; Unexpected change in commodity prices; Economic management rating; Agarwala price distortion index; GNP; Adult literacy.	No
Khwaja (2009)	Project performance and community-specific constraints; sample: Community-maintained infrastructure projects in Northern Pakistan; n=99;	Found that the community-specific constraints do matter in project success, but their impact can be mitigated by better project design.	Project total score; Project complexity; New project dummy; Government project dummy; Project leader exists; Leader quality; Project age; External funds in the project; Project share inequality; Community variables.	No
Mubila et al. (2002)	Determinants of project success in ADB; sample: ADB projects; n=146, up to 1995	Used simple OLS as well as probit models. Found that the rates of return at appraisal are at best weak indicators of project success for the studied projects.	Project success indicator; Economic rate of return; Sector; Project size; Cost overrun; Export/GDP ratio; Inflation; GDP growth; Population size; GNP per capita; Human Development Index.	No
Dobrescu et al. (2008)	Determinants of project success in	Found that private participation without commercial risk tends to	Total delay; Sign to disbursement; Political delays; Tariff covenants respected;	Yes (used IV approach for sovereign guarantees and

Scholar(s)	Topic & Sample	Contribution	Variables	Selection bias addressed
	EBRD infrastructure projects; sample: EBRD infrastructure projects; n=90; 1993-2005	increase project success. Also, found that private participation with commercial risk has no significant effect on project performance. Sovereign guarantees reduce delays but also decrease financial discipline.	Financial covenants respected; Private-sector participation with risk; Sovereign guarantee; District heating; Waste water; Regional dummies; Total investment; EBRD share; Municipal client; PSA; Municipal guarantee; No. of investors; Works or turnkey realised; Central participation; Private-sector participation with risk planned; Years since transition; EBRD transition indicator; BEEPS index; Project age.	municipal guarantees. For the former: the number of years in transition at the time of project signing; the project age and the BEEPS indicator of quality of business environment. For the latter: whether the private sector participation was planned at the design stage; the respective shares of central and municipal governments' investments in the project)
Honig (2014)	Organizational autonomy and country context in driving project success; sample: n=14,000 from 9 international development organizations	Organizational autonomy matters to project success, with increasing returns to autonomy in fragile states and in project domains where it is more difficult to externally observe outcomes. Organizational features such as bureaucratic delivery channels have an important role to play in the variance of outcomes.	Project success (An ordinal variable ranging from 1-6. Used after z-transformation to allow to fit OLS models); State fragility index; Project size; Autonomy (1); Autonomy (2); Sector; Internal Evaluation; Independent Evaluation Office; Commitment to Development Index; Quality of Official Development Assistance.	No

Exhibit OA1: Empirical set-up

Exhibit OA1.1: Project selection bias

Although several selection bias correction procedures are now available to use, there is no agreement among scholars as to which one is the most effective. Stolzenberg and Relles (2011) claimed that there is currently no tool which offers a general solution to the selection bias. Similarly, Winship and Mare (1992) reviewed a number of these techniques and concluded that none of them works well all the time.

In this paper, Heckman selection bias method is used. It is limited to situations in which the choices are binary which suits this paper well due to the way the TI project success variable is derived. Also, this method helps with the selection bias due to unobservables which are at play here. It uses the inverse Mills ratio to take account of the selection bias. It is a two-stage model in which the probability of selection at the first stage is estimated and then the possible selection bias is removed at the second stage where the inverse Mills ratio is added as the additional variable. The probit model assumes that the error term follows a standard normal distribution.

Specifically, the binary response model with sample selection is firstly tested, following Heckman's (1979) notation:

$$y_1 = 1[x_1\beta_1 + u_1 > 0] \qquad \textit{Eq. (1)}$$
$$y_2 = 1[x_1\delta_2 + u_1 > 0], \qquad \textit{Eq. (2)}$$

where y_1 (project success) is observed only if y_2=1 (project selection), and x_1 (explanatory variables explained below) and at least one more variable (project expired dummy as explained in Appendix 5). In this case, probit estimation of β_1 (i.e. range of project- and client-related explanatory variables) based on the selected sample will lead to inconsistent results unless error terms u_1 and u_2 are uncorrelated as argued by Heckman (1979). Further details behind selection bias modelling are included in Appendix 5.

In terms of the main area for hypothesis testing which is based on the outcome equation only, the probability of project success can be expressed as follows:

$$p_i = Prob\left(Y_i = 1 \middle| X = \int_{-\infty}^{x_i'\beta} (2\pi)^{-1/2} \exp(-\frac{t^2}{2}\right) dt = \phi(x_i'\beta) \qquad \textit{Eq. (3)}$$

where ϕ is the cumulative distribution function of a standard normal variable which ensures 0 $\leq p_i \leq$ 1, x is a vector of factors that explain the variation in probability of success and β is a vector of parameters that reflects the effect of changes in x on the probability of success. The elements of vector x represent the independent variables in the model, namely project- and client-related characteristics.

There are several specification issues which need to be addressed before running Heckman selection model. Firstly, as explained by Puhani (2000), when the same variables are used to model the selection and outcome equations, as well as when exclusion restrictions are not utilized, the model is only identified by the non-linearity inherent in the inverse Mills ratio.

This does not apply here as the range of variables used in the selection equation differs from the variables captured in the outcome equation.

As for the exclusion restrictions, the inverse Mills ratio and the X vector in the outcome equation will be less correlated when exclusion restriction is present. This could also help in reducing multicollinearity among predictors as well as the correlation between error terms as argued by Puhani (2000). Here, the chosen exclusion restriction variable is “expired project” dummy.[1] It refers to the projects which did not receive Board approval after 12 months period since their structure review and have not been re-approved within a further 12 months which leads to their cancellation. Based on the pull of cancelled projects collected for the selection equation, i.e. 2,035 projects, the expired projects consisted of 53% of the overall sample. Based on the manual checks as well as confirmation from EBRD Ops Com Secretariat, none of the expired projects were re-cycled under a different project ID.

From the conceptual side, there are several factors which could explain the fact that some projects expire. The most likely reason is linked to the transparency of information. The due diligence procedure carried out by EBRD Banking department may be time consuming due to the difficulties with the client who may, for instance, not disclose the required information in a quick and effective manner. Another reason could be the complexity of the project, e.g. use of a new financing instrument, blended financing solutions, all of which may prolong the length of the project assessment. Based on the selected review of the expired projects, the most frequent argumentation behind projects falling under ‘expire status’ is the complexity of the due diligence process, particularly for these projects which required environmental impact assessment.[2]

Another common specification error is a failure to properly correct for mis-estimated standard errors. As stated by Heckman himself, ‘the standard least squares estimator of the population variance is downward biased’ and therefore ‘the usual formulas for standard errors for least squares coefficients are not appropriate except in the important case of the null hypothesis of no selection bias’ (Heckman, 1976, pp. 157-158). As a result, researchers need to correct these standard errors using a consistent errors estimator which is often referred to as robust standard errors. In this paper, this is addressed by running all the regression specifications with the ‘vce robust’ option which uses the robust estimator of variance. This could partially resolve the issue as this estimator is robust to some types of misspecification as long as the observations are independent.

Lastly, Rodman (2009)’s CMP module for estimating fully observed recursive mixed-process models was used as an alternative set-up to test the selection bias specifications with a wider range of explanatory variables on both sides of the equations, in particular country-level controls. The rationale for this is the fact that there have been too many additional variables

[1] An alternative exclusion restriction candidate was considered, namely the ‘new client’ indicator. This has been defined as a dummy indicating that the client is new to EBRD. Unfortunately, this candidate has been rejected for two reasons. Firstly, from the conceptual perspective, the fact that the client is new to the bank is likely not just to drive the allocation to the signed projects, but also it is expected to influence the project success probability. This is because the new clients are likely to be riskier to deal with as well as require more resources, all of which may impact the probability of project success. Secondly, from the practical perspective, the aggregate mapping of client’s novelty to the bank has proved to be almost impossible due to the lack of comprehensive mappings of client’s ownership structure stored at the bank in aggregated and comparable manner.

[2] There is no possibility that the ‘expire status’ of a project is an outcome of a strategic decision by any of the counterparties to delay the approval of the project till more suitable timing or condition is being met.

that did not enter the selection equation which made the Heckman selection model unstable and failing to converge.

Exhibit OA1.2: Indirect effects - moderated mediation analysis

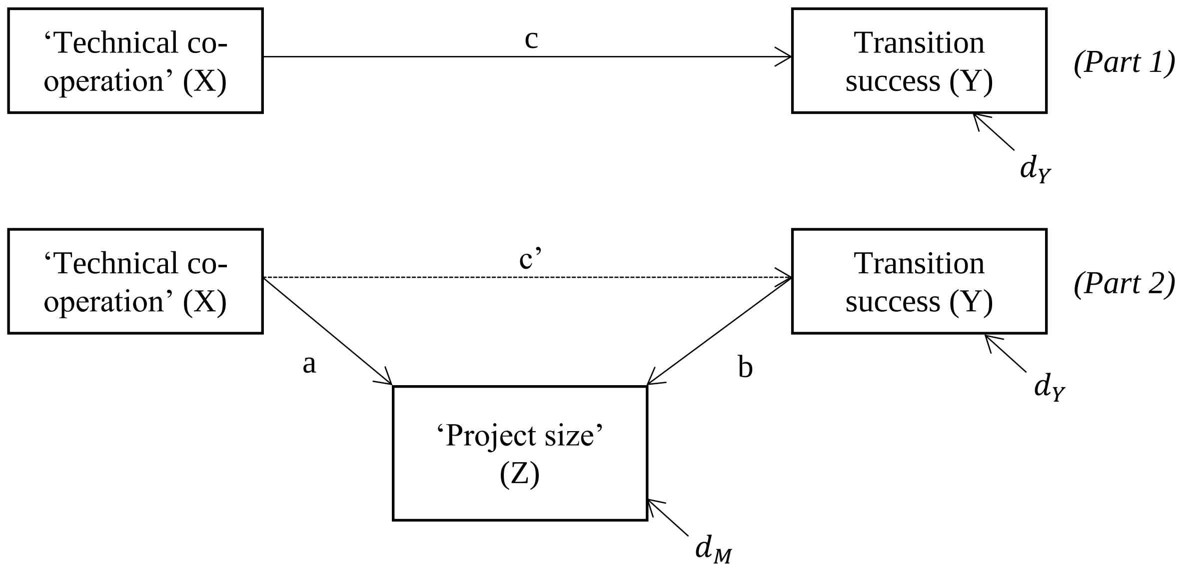
As inferred from the initial analysis of this topic, some variables, and in particular ‘project size’, may impact the probability of project success through indirect channels. For this reason, a special focus is dedicated to the indirect effects through which project - as well as client – factors may influence the dependent variable. This is firstly assessed through simple interaction terms and then followed by the moderated mediation modelling technique which is explained here.

As argued by Imai et al. (2010), mediation analysis plays an essential role in overcoming the limitation of any casual mechanisms, namely not telling how and why a treatment casually affects an outcome. Mediation analysis can help to identify intermediate variables, i.e. ‘a moderator variable’, that lie in the casual pathway between the treatment and the outcome. A moderator variable is defined a variable involved in an interaction with another variable in the model such that the effect of the other variable depends upon the value of the moderator variable (Judd and Kenny, 1981). This is often referred to as a conditional indirect effect, i.e., the value of the indirect effect is conditional on the value of the moderator variable.

Chart OA1 illustrates the concept of moderation mediation mechanisms between two variables - ‘project size’ as a potential moderator variable and ‘technical co-operation’ dummy as a potential treatment variable. When mediation occurs the c’ path in Part 2 of the chart is smaller than the c path in Part 1. As explained by Judd and Kenny (1981) as well as Baron and Kenny (1986), the first step is to establish that there is an effect that may be mediated and then to show that X is related to M by estimating the coefficient a in Part 2. The third step is to show that M is related to Y while X is held constant. The final step is to estimate and to test the path c’ in Part 2 to determine if the data are consistent with complete mediation. If the data suggest that c is nonzero but its analogue c’ in the multiple regression does not differ from zero, then it could be concluded that complete mediation has occurred according to Kenny et al. (1998).

Until recently, researchers wishing to test the significance of indirect effect had to manually follow the outlined steps which involved running multiple regressions and using Sobel’s (1982) large-sample test to confirm any findings. Fortunately, developments in statistical theory provide automated methods for testing indirect effects in mediation models with various mediation analysis programmes available in Stata, e.g. paramed (Emsley et al., 2012), ldecomp (Buis, 2010), medeff (Hicks and Tingley, 2011) and gformula (Daniel, De Stavola and Cousens, 2012). Here, medeff is used as it is superior to some of the other codes due to sensitivity analyses, medsens, which can be ran simultaneously with this programme.

Chart OA1: Applied path models showing total effect (Part 1) and mediated effect (Part 2) of X ('technical co-operation') on Y ('probability of full transition success').



Source: Shrout and Bolger (2002) - concept; Author (2017) - application.
Notes: Residuals terms are displayed as "*d*" effects.

Specifically, the 'medeff' and 'medsens' commands contained in the mediation package implement the procedures described in Imai, Keele, and Tingley (2010) and Imai, Keele and Yamamoto (2010) for a common set of statistical models. The calculation of how much of the treatment variable is transmitted by the mediating variable lies at the heart of this programme. Following Robins and Greenland (1992), the indirect effects, or casual mediation effects, for each unit i is:

$$\delta_i = Y_i\{t, M_i(1)\} - Y_i\{t, M_i(0)\}$$

for each treatment status t = 0, 1. This casual quantity is the change in the outcome corresponding to a change in the mediator (e.g. 'project size') from the value that would be realized under the control condition, $M_i(0)$, to the value that would be observed under the treatment control, $M_i(1)$, while holding the treatment status (e.g. technical co-operation) constant at t. For example, if $M_i(1) = M_i(0)$, then the treatment has no effect on the mediator and the causal mediation effect would be zero.

Medeff was also selected as it comes in handy after conducting mediation analysis due to the incorporated sensitivity analysis option called medsens.[3] The limitation of this option is that it does not handle the interaction between pre-treatment x variables for either the treatment or mediator. Also, a requirement for casual mediation analysis with this option is that the same observations are used in the mediator and outcome regressions which was not too restrictive in the applied specifications as explained in the results section.

[3] Medsens employs the correlation (Rho) between the residual variances (errors) of the models for the mediator and outcome and its effects are computed given different fixed values of the residual covariance. The proposed sensitivity analysis answers the question of how large does Rho have to be for the mediation effect (ACME) to disappear.

Exhibit OA1.3: Potential endogenous regressors in the outcome equation

The last empirical set-up was triggered by the observation that some elements of 'project size' could be endogenous, and so may be correlated with the error terms. In addition, the latent error term ε may be heteroskedastic (e.g. some regressors could have random coefficients) and has an unknown distribution as argued by Dong and Lewbel (2015). There is a wide range of potential methods for estimating such models, e.g. maximum likelihood, control functions and frequently used IV approach, which in this case would require ivprobit with a valid instrument for 'project size'.

There are strict conditions which instruments must satisfy in order to be valid for IV application as outlined by Dong and Lewbel (2015), e.g. i). they must themselves satisfy orthogonality conditions (E[uZ]=0); ii). they must exhibit meaningful correlations with X; and iii). they must be properly excluded from the model, so that their effect on the response variable is only indirect. Unfortunately, there are no good instruments available for 'project size' to test in this paper which would fulfil any of these conditions.

Many scholars investigating project success factors among other MDBs faced similar issues. For instance, Denizer et al. (2013) in their paper on factors driving project success of World Bank investments faced the exact problem of lacking a good instrument which, as they explained would be difficult for them to justify classification of some variables as instruments that influence project outcomes only through their effects on other potentially endogenous variables with no direct effects on outcomes. For this reason, they have decided to quantify the magnitude of the likely biases on their OLS estimates due to these unobserved, and potentially confounding, effects. For this, they used Bayesian methods to formally specify a range of reasonable prior beliefs about the importance of these confounding variables, and then explored quantitatively how much these priors influence posterior inferences about the slope coefficients of interest. Unfortunately, this method cannot be applied here due to the binary nature of the outcome equation.

The method which is chosen for this paper is the approach based on Lewbel's (2012) idea for instrumental variables estimation using heteroscedasticity-based instruments. His approach aims to identify structural parameters in regression models with endogenous regressors in the absence of traditional identifying information, i.e. a good external instrument. As he explained, the identification is achieved in this context by having regressors hats that are uncorrelated with the product of heteroskedastic errors, which is the feature of many models where error correlations are due to unobserved common factor (Lewbel, 2012). Lewbel's model can be applied when no external instruments are available, or, alternatively, used to supplement external instruments to improve the efficiency of the IV estimator.

In its simplest version, the Lewbel's model allows for construction of generated instruments from the auxiliary equations' residuals, multiplied by each of the included exogenous variables in mean-centered form: $Z_j = \left(X_j - \bar{X}\right) * \in$, where $\in$ is the vector of residuals from the 'first-stage regression' of each endogenous regressor on all exogenous regressors, including a constant vector.

Identification in Lewbel's model is achieved by restricting correlations of errors with X. This relies upon higher moment, and is likely to be less reliable than identification based on coefficient zero restrictions. However, in the absence of plausible identifying restrictions for 'project size', this approach is the only reasonable strategy to use in this paper.

Table OA2: Heckman sample selection modelling – regression results

	Model A: Heckprobit (without country-level controls)			Model B: Heckprobit (with country-level controls)			Model C: Two-stage Heckman (with country-level controls)				Model D: Heckprob with CMP module		
	Outcome equation		Selection equation	Outcome equation		Selection equation	First stage (selection equation)		Second stage (outcome equation)		Outcome equation		Selection equation
	Raw	Margins*	Raw	Raw	Margins*	Raw	Raw	Margins	Raw	Margins	Raw	Margins	Raw
Project size (ln)	0.062	0.021	0.083**	0.0939**	0.035***	0.036	0.043	0.014	0.0948*	0.0336*	0.115*	0.038	0.043
	(0.050)	(0.016)	(0.037)	(0.039)	0.011	(0.034)	(0.035)	(0.012)	(0.037)	(0.014)	(0.062)	0.023	(0.030)
Effectiveness delay	-0.013	-0.005	n/a	0.007	0.002	n/a	n/a	n/a	0.007	0.003	0.040	0.013	n/a
(srt)	(0.054)	0.020	-	(0.062)	0.022	-	-	-	(0.063)	(0.022)	(0.051)	0.018	-
Preparation time (srt)	0.043	0.016	n/a	0.015	0.005	n/a	n/a	n/a	0.015	0.005	-0.009	-0.003	n/a
	(0.068)	0.025	-	(0.063)	0.023	-	-	-	(0.063)	(0.022)	(0.064)	0.021	-
Framework (1=yes)	0.121	0.045	n/a	0.202	0.072	n/a	n/a	n/a	0.205	0.073	0.238	0.080	n/a
	(0.127)	0.046	-	(0.146)	0.052	-	-	-	(0.151)	(0.052)	(0.163)	0.058	-
Technical assistance	0.356	0.099	1.573***	0.232	0.146	1.527***	1.543***	0.508***	0.256	0.091	0.281	0.094	1.546***
(1=Yes)	(0.613)	0.066	(0.141)	(0.741)	0.108	(0.137)	(0.134)	(0.045)	(0.770)	(0.274)	(0.532)	0.194	(0.186)
Co-fin w/t others	0.008	0.003	n/a	-0.077	-0.027	n/a	n/a	n/a	-0.078	-0.028	-0.056	-0.019	n/a
(1=Yes)	(0.115)	0.043	-	(0.126)	0.046	-	-	-	(0.130)	(0.046)	(0.152)	0.051	-
Equity instrument	-0.243	-0.082	-0.467***	-0.158	-0.079	-0.49***	-0.50***	-0.16***	-0.170	-0.061	-0.181	-0.062	-0.497***
(1=Yes)	(0.210)	0.053	(0.066)	(0.339)	0.058	(0.065)	(0.061)	(0.021)	(0.332)	(0.122)	(0.293)	0.111	(0.092)
Client's PD	-0.152	-0.060*	0.199***	-0.148	-0.045	0.198***	0.198***	0.065***	-0.146	-0.052	-0.062	-0.021	0.199***
	(0.153)	0.035	(0.032)	(0.154)	0.033	(0.035)	(0.036)	(0.011)	(0.168)	(0.059)	(0.117)	0.037	(0.026)
Client as state (1=Yes)	-0.289*	(0.101)	-0.311**	-0.302*	-0.119	-0.259*	-0.267	-0.088	-0.307	-0.109	-2.439	-0.087	-0.213
	(0.156)	0.070	(0.124)	(0.171)	0.081	(0.141)	(0.138)	(0.046)	(0.162)	(0.057)	(1.666)	0.115	(0.603)
Expired dummy	n/a	n/a	-7.428***	n/a	n/a	-7.46***	-7.424**	n/a	n/a	n/a	n/a	n/a	-5.424*
(1=Yes)	-	-	(0.205)	-	-	(0.186)	(0.198)	-	-	-	-	-	(0.268)
/athrho)		n/a	0.093		n/a	-0.190	n/a	n/a	n/a	n/a	n/a	n/a	-0.211
		-	(0.781)		-	(1.064)	-	-	-	-	-	-	(0.667)
rho		n/a	0.092		n/a	-0.187	n/a	n/a	n/a	n/a	n/a	n/a	-0.208
		-	(0.774)		-	(1.027)	-	-	-	-	-	-	0.359
Inverse Mills Ratio	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	-0.156	-0.055	n/a	n/a	-0.638
	-	-	-	-	-	-	-	-	(1.081)	(0.381)	-	-	-

	Model A	Model B	Model C: First stage	Model C: Second stage	Model D
Clusters	Concept year x Project ID	Concept year x Project ID	Concept year x Project ID	Concept year x Project ID	[not allowed]
VCE	Robust	Robust	Robust	Robust	Robust
Observations	2,611	2,213	1,494	1,093	1,494
Pseudo R2	n/a	n/a	0.1433	0.0678	n/a
Wald chi2	0.62	0.03	1778.05	14223.23	n/a
LR chi2	n/a	n/a	n/a	n/a	346.71
Prob > chi2	0.4306	0.8586	0.000	0.000	0.000
Log pseudolikelihood	-1406.807	-1223.24	-863.897	-368.273	-1217.05

Source: Author's calculation (2017).

Notes: This table reports regression results from four sample selection models.

Models A and B use heckprobit technique which fits maximum-likelihood probit models with sample selection. Outcome equation refers to the analysed sample of 1,573 signed and completed projects. Selection equation refers to the sample of 2,034 projects which were rejected or cancelled. The allocation variable used in these models is coded as 0 or 1, indicating an observation not selected (selection equation) and 1 indicating a selected observation (outcome equation). Margins are calculated on the probability of success conditional on selection [Pr(achieved=1|outcome=1), predict(pcond)]. Both heckprobit models report robust standard errors as specified with the vce(robust) option. This results with computation of the Wald test which is reported at the end of the outputs instead of a likelihood-ratio test. The exclusion restriction used in the selection equation is 'expired' project dummy variable. The difference between Models A and B is the fact the latter uses a range of country-level controls.

Model C applies two-stage Heckman procedure with the same range of county-level controls as per Model B. Here, the regressions are fitted with selection using Heckman's two-step consistent estimator. The first stage results show the first-step probit estimates of the selection equation. Average marginal effects are obtained and displayed in a separate column. The second stage results show the second-step probit estimates of the outcome equation. It also includes the inverse Mills ratio calculated after fitting the first stage of this model. Average marginal effects are obtained and displayed in a separate column.

Model D expands Model B with additional county-level controls as well as interaction terms to further test the results. The user-defined Stata routine cmp described in Rodman (2009) is used due to issues with model convergence. Similarly, margins are calculated on the probability of success conditional on selection [Pr(achieved=1|outcome=1), predict(pcond)]. Robust standard errors are reported as specified with the vce(robust) option. This results with computation of the Wald test which is reported at the end of the outputs instead of a likelihood-ratio test. The exclusion restriction used in the selection equation is 'expired' project dummy variable which is consistent across all models.

Robust standard errors are clustered by concept review year – project ID in all models (except Model D where clustering is not allowed) and are shown in parentheses. The display of the following variables is omitted: sector and regional dummies (all models), country-level controls (all models except Model A) interaction terms (Model D only), constant (all models). ***(**)(*) denote significance at the 1 (5) (10) percent level.