# Recalibrating the Reported Returns to Agricultural R&D:

# What if We All Heeded Griliches?

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## ABSTRACT

The statistic of choice used by analysts assessing the economic returns to agricultural research is an internal rate of return (IRR)—93 percent of the 2,829 evaluations reported in version 3.0 of the InSTePP returns-to-research database. The mean IRR is 59.6 percent per year, resulting in entirely implausible economic implications if this return were interpreted as a conventional compounding interest rate. Building off recent conceptual and empirical simulation work that finds in favor of using a modified internal rate of return (MIRR, or its empirical equivalent, a benefit-cost ratio, BCR) to summarize the returns to agricultural research, we were able to recalibrate 2,208 of the published IRR estimates. The resulting median BCR is 24.8:1 and the MIRR is 16.9 percent per year (conditional on a research lag length of 30 years, and a discount rate of 10 percent), well less than the corresponding 63.2 percent per year mean IRR. We also show that the ranking of various agricultural research investments using IRRs versus MIRRs is very different. Moreover, the differences in the rankings shrink when the discount rate used to calculate the MIRR approaches the IRR, but the differences remain large when using a discount rate whose magnitude is the same as that commonly used in the literature for calculating BCRs.



**Keywords —** modified internal rate of return, benefit-cost ratio, research and development

**JEL codes** — Q16, Q18, O22



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## Recalibrating the Reported Returns to Agricultural R&D:

## What if We All Heeded Griliches?

The International Science and Technology Practice and Policy (InSTePP) center at the University of Minnesota has compiled an extensive database of rate of return estimates for investments in food and agricultural R&D dating back to Zvi Griliches's seminal analysis of hybrid corn (Griliches 1958). This returns-to-research database (version 3.0) includes 2,829 evaluations from 492 studies published from 1958 to 2015.[1] The predominant metric used to quantify these returns is the internal rate of return (IRR) (94 percent of studies and 93 percent of evaluations). The benefit-cost ratio (BCR) has also been used, but much less often (34 percent of studies and 28 percent of evaluations). Some studies have reported both the IRR and BCR (28 percent of studies and 21 percent of evaluations). Critiques of using the IRR to measure the value of an investment date back to Griliches's seminal paper (e.g., Hirshleifer 1958) and continue to the present (e.g., Hurley, Rao and Pardey 2014 and 2016a). Similarly, defenses of the utility of the IRR date back to Griliches's seminal paper (e.g., Bailey 1959) and continue to the present (Oehmke 2016). While Griliches reported IRRs in addition to BCRs in his original study, he questioned the sensibility of using an IRR to represent the returns to hybrid corn research noting that his "…objection to this particular procedure is that it values a dollar spent in 1910 at $2,300 in 1933…I prefer to value the 1910 dollar at a reasonable rate of return on some alternative social investment (Griliches 1958, p. 425)."

[1] For a description of the methods used to compile this database and a listing of all the published data sources, see http://www.instepp.umn.edu/sites/default/files/product/downloadable/Pardey%20et%20al%202016%20--%20InSTePP%20RTR%20v3.0%20documentation%2826OCT2016%29_2.pdf.

The vast majority of evaluations in the InSTePP database (80 percent) are *ex post* evaluations of completed projects or programs, funded primarily through public sources (98 percent). The purpose of these studies is to provide information to policy makers about the profitability of such investments relative to other investments that could be made. While the IRR provides a useful metric for determining whether or not an investment is profitable, it is not typically recommended by textbooks for comparing the relative profitability of investments (Kierulff 2008; Daunfeldt and Hartwig 2014).[2] Even so, research has consistently found the IRR is a commonly used metric that is used in conjunction with other metrics by private business when making investment decisions (Graham and Harvey 2001; Ryan and Ryan 2002; Truong, Partington, and Peat 2008; Bennouna, Meredith, and Marchant 2010; Daunfeldt and Hartwig 2014). One explanation for its attractiveness as a metric is its interpretability as a percentage (Burns and Walker 1997), much like the annualized percentage rates of growth commonly reported for a range of financial products (e.g., mortgages, certificates of deposit, and mutual funds). However, Hurley et al. (2014) showed how interpreting the IRR as an annualized percentage rate of return can lead to incredible implications, and instead recommended the use of the modified internal rate of return (MIRR) which is reasonably interpreted as an annualized percentage rate of return.

Hurley et al. (2016a) showed that with a consistent set of assumptions, the MIRR and the BCR yield a consistent ranking of alternative investments where higher MIRRs and BCRs reflect more desirable investments. It is straightforward to construct examples that show the BCR and IRR, and therefore the MIRR and IRR, will not always consistently rank investments. This raises a policy pertinent question. How would the ranking of various agricultural R&D

[2] Alston, Norton and Pardey (1995, p. 33) noted that “According to this [IRR] criterion, programs are profitable if the IRR is greater than the opportunity cost of funds.”

investments compare had authors heeded Griliches's concerns and used the BCR or, analogously, the MIRR, instead of the IRR? Additionally, how would the distribution of these rates of return compare when using the BCR or the MIRR with its annualized percentage rate of return interpretation instead of the IRR? The purpose of this paper is to answer these two questions.

## 1. Rate of Return Metrics for Agricultural R&D

Researchers typically characterize the stream of costs and benefits associated with agricultural R&D projects and programs using four dates. Figure 1 illustrates. The first date (0 in Figure 1) is the date that resources actually start to be invested into the project or program and reflects expenditures. These expenditures often span a period of time, at first growing, then declining, and eventually leading to a second date that signifies the point at which these expenditures cease—$T_c$ in Figure 1. The third date is the date when innovations resulting from these investments begin to reap benefits in terms of increased productivity or reduced costs for example—$T_b$ in Figure 1. As with the investment's expenditures, returns tend to initially grow over time, but eventually start to shrink and even cease as new innovations replace the old—$T$ in Figure 1. On average, evidence gleaned from the 2,418 evaluations summarized in Table 1 has benefits beginning 6.1 years after the initiation of research costs, cost streams that run over 22.7 years, and benefits that accrue for 30.8 years after the initiation of the research. Table 1 also shows there is considerable variation in these various components of the overall research lag around the sample averages.

[Figure 1: *Illustrative Research Cost and Benefit Streams*]

[Table 1: *Research Lags, Ts, and Discount Rates, δs, from the Published Evaluations*]

Within this framework, the present value of the investment's expenditures or research costs is defined by the sum $PVC(\delta_c) = \sum_{t=0}^{T_c} c_t(1+\delta_c)^{-t}$ where $c_t \geq 0$ is the research cost $t$ years from the project's initiation and $\delta_c > 0$ is a discount rate that reflects the time value of money or opportunity cost of the resources acquired to finance the project. The present value at year zero of the return on investment or research benefit is defined by the sum $PVB(\delta_b) = \sum_{t=T_b}^{T} b_t(1+\delta_b)^{-t}$ where $b_t \geq 0$ is the research benefit $t$ years from the project's initiation and $\delta_b > 0$ is a discount rate that reflects the time value of money or opportunity cost of investing these returns elsewhere. These present value formulas can be used to define the IRR, BCR and MIRR. The IRR makes these two net present value formulas equate: $PVC(\text{IRR}) = PVB(\text{IRR})$. The BCR is just the ratio of the two: $BCR(\delta) = PVB(\delta)/PVC(\delta)$. Unlike the IRR, some assumption about $\delta$ is required to compute the BCR. When the same discount rate is used for an investment's expenditures and economic returns, both Athanasopoulos (1978) and Negrete (1978) showed the MIRR is just a transformation of the BCR: $MIRR(\delta, T_e) = \sqrt[T_e]{(1+\delta)^{T_e} BCR(\delta)} - 1$.[3] The precise interpretation of this $MIRR(\delta, T_e)$ is that it is the annualized rate of return for an investment of $PVC(\delta)$ at the project's initiation that returns the value $(1+\delta)^{T_e} PVB(\delta)$ at $T_e$ years following the project's initiation. As with the BCR, some assumption on $\delta$ is required to calculate the MIRR. However, an additional assumption on $T_e$ is also needed to calculate the MIRR.

## 2. Rate of Return Rankings

[3] The literature often defines the modified internal rate of return more generally: $MIRR(\delta, T_e) = \sqrt[T_e]{(1+\delta_b)^{T_e} PVR(\delta_b)/PVC(\delta_c)} - 1$, where $\delta_b$ does not necessarily equal $\delta_c$. Here we employ the less general definition (where $\delta_b$ equals $\delta_c$) for two reasons. First, the questions of interest can be reasonably answered with the less general definition. Second, the less general definition is not subject to several of the criticisms of the MIRR in Oehmke (2016) that could distract from our primary purpose.

Hurley et al. (2016a) showed that $BCR(\delta)$ and $MIRR(\delta, T_e)$ will rank projects identically as long as all projects are evaluated using the same $\delta$ and $T_e$.[4] As the choice of $\delta$ used to calculate the BCR in the agricultural R&D literature has varied over time (from 2 to 15 percent per year, see Table 1), the comparison of BCRs across studies should be made with the caveat that the results could be due to differences in the relative timing and magnitude of the investments' expenditures and economic returns or it could be attributable to differences in the rate at which the investments' expenditures and economic returns were discounted. Alternatively, by comparing projects using the same discount rates, the explanation of the result is less confounded and can be directly attributed to the timing and magnitude of the investments' expenditures and economic returns.

Figure 2 shows how the ranking of the 412 evaluations in the InSTePP database that report both IRRs and BCRs compare using the reported IRR and the imputed MIRR calculated using the discount rates reported in the original studies and setting $T_e$ equal to the $T$ reported in the original study. Panel a) shows the scatter plot of IRR and MIRR rankings along with the linear line of best fit. This line of best fit explains 63 percent of the variation in the rankings. The line's positive intercept and slope of less than one implies that the MIRR ranks projects with a high IRR lower and projects with a low IRR higher on average. If they ranked projects identically, the intercept would be zero and slope would be one. This trend is further highlighted in Panel b), which shows the difference between the rank based on the MIRR and the rank based on the IRR arranged according to the IRR's rank. What is more evident in Panel b) is that there are very large differences in rankings, over 200 places in several circumstances and commonly over 100 places when only 412 projects are being ranked.

[4] See also Robinson et al. (2015).

[Figure 2: *Reported IRRs versus MIRRs Using the Study's BCRs and T for* $T_e$]

The discount rates and $T_e$ used to calculate the MIRRs for the analysis in Figure 2 differ widely across evaluations. To focus on how differences in the timing and magnitude of the projects' expenditures and economic returns affect the relative ranking of projects, we used the methodology reported in Hurley et al. (2014) to approximate the MIRRs for a common discount rate and $T_e$ equal to 30. Figure 3 and 4 show the same results as Figure 2, with the MIRRs imputed using annual discount rates of 5 and 20 percent, respectively.[5]

[Figure 3: *Reported IRRs versus Imputed MIRRs Using* $T_e$ *of 30 and* $\delta$ *of 0.05*]

[Figure 4*: Reported IRRs versus Imputed MIRRs Using* $T_e$ *of 30 and* $\delta$ *of 0.2*]

With a 5 percent discount rate, the line of best fit between the IRR and MIRR only explains 44 percent of the variation in ranks (Figure 3a). Alternatively, 91 percent of the variation in ranks is explained with a discount rate of 20 percent (Figure 4a). In both cases, the intercept of the line of best fit is positive, while the slope is less than one. Again, this implies that the ranking based on the MIRR is lower for higher IRRs and higher for lower IRRs on average. The maximum difference in rankings reached nearly 300 and again commonly exceeds 100 when using an annual discount rate of 5 percent (Figure 3b). With an annual discount rate of 20 percent, the difference in rankings is much less pronounced with a maximum around 150 (Figure 4b).

Hurley et al. (2014) showed the IRR and MIRR are equal when the discount rate used to evaluate the MIRR equals the IRR. With an average and median IRR of 63.2 percent per year and 38 percent per year respectively for the 412 evaluations with both IRRs and BCRs, increasing the annual discount rate from 5 to 20 percent tends to reduce difference between the

[5] For discount rates between 5 and 20 percent, the results are monotonic.

discount rate and IRR, thus making the IRR and MIRR ranking results increasingly consistent. With that said, 20 percent represents the maximum annual discount rate used by studies in the InSTePP database to calculate BCRs, while 5 percent per year is a commonly used social discount rate and the first quartile of the discount rates used to calculate BCRs in the InSTePP database. Thus, the revealed preferences of returns-to-research analysts favor results more like those reported in Figure 3 over Figure 4.

## 3. Returns-to-Research Distributions

### 3.1 Modified Internal Rate of Return Distributions

To derive MIRR estimates corresponding to the 2,208 IRR estimates reported in the InSTePP database we deployed a three-step procedure. The first step was to take the 412 analytically-derived MIRR estimates reported in Hurley et al. (2014) obtained from the sub-set of returns-to-research studies that reported both a BCR and a corresponding IRR. The second was to deploy regression methods to identify the best-fitting relationship between the reported IRRs and the 412 derived MIRRs while also accounting for differences in $T_c$, $T_b$, and $T$. Finally, these regression results were used to estimate conditional MIRRs given the 2,208 reported IRR values.[6] Analytically the MIRR can be related to IRR by way of the BCR in the manner described by Hurley et al. (2014), specifically:

$$MIRR = \sqrt[T]{\frac{\sum_{t=0}^{T} w_{c_t}(1+IRR)^{-t}}{\sum_{t=T_b}^{T} w_{b_t}(1+IRR)^{-t}} \frac{\sum_{t=0}^{T} w_{b_t}(1+\delta^r)^{T-t}}{\sum_{t=0}^{T} w_{c_t}(1+\delta^c)^{-t}}} - 1$$

[6] The combined Kolmogorov-Smirnov test for equality of estimation sample (412) and projection sample (1,796), is 0.179 with a P-value < 0.000 indicating that the two distributions are not equal. Furthermore, the one-sided test and summary statistics (e.g., the median and percentiles) suggest that the projection sample lies to the right of the estimation sample.

where $w_{c_t}$ and $w_{b_t}$ are the distributional parameters of the cost and benefit streams at time $t$, which are usually not reported in original evaluation studies. The evident intricate relationship between IRR and MIRR entails a non-linear transformation for regression analysis, thus the convenient logarithmic transformation is used. Visually inspecting a scatter plot between the IRRs and MIRRs (both in the log form) suggests that a linear functional form may be plagued by outliers. Instead of excluding these evaluations from the regression, we explore various robust regression estimators, such as the M-estimator (Huber 1973), MM-estimator (Yohai 1987), and the quantile estimator, in addition to the ordinary least squares estimator, to derive robust and efficient estimates. Our comparisons show that these various estimation models are not only similar in terms of parameter estimates and statistical significance, but also in terms of the summary statistics for MIRRs projections using the full sample (see Table A1, Supplementary Material). For simplicity and ease of interpretation, only the ordinary least square results are reported in Table 2. These results were obtained separately for four different annual discount rates—specifically 5, 10, 15, and 20 percent, spanning the range of rates in the InSTePP database) and a $T_e$ of 30 (the average $T$ in the InSTePP database) when calculating the MIRR. The regression estimates are all highly significant and of the expected sign. The percentage of variation explained by the regressions ranges for 54 percent with a 5 percent per year discount rate to 85 percent with a 20 percent per year discount rate, which again reflects the nature of the returns-to-research evidence and the fact that the MIRR approaches the IRR as the discount rate used to calculate it approaches the IRR.

[Table 2: *Regression Results Relating MIRR to IRR*]

The full sample of IRRs was used with the regression results in Table 2 to project MIRRs for four different discount rates and $T_e$ equal to 30. The distributions of these projected MIRRs are compared with the distribution of IRRs in Table 3. The mean rate of return based on the 2,208 IRRs in the InSTePP database is 63.2 percent per year with a standard deviation of 175.6, median of 38.0 and inter-quartile range of 40.3. The mean rate of return based on the MIRR with a 10 percent annual discount rate is 17.8 percent per year with a standard deviation of 5.3, median of 16.9 and interquartile range of 5.2. Increasing the discount rate used to calculate the MIRR increases the mean, standard deviation, median and interquartile range. Still, even with an annual discount rate of 20 percent the mean MIRR is 24.8 percent per year—with a standard deviation of 5.6, median of 24.0 and interquartile range of 6.2—well below the corresponding mean IRR of 63.2 percent per year.

[Table 3: *Descriptive Statistics, Reported IRRs and Imputed MIRRs*]

The mean (and median) imputed MIRRs increases as the annual discount rate increases, from 14.3 percent per year with $\delta$ = 5 to 24.7 percent per year with $\delta$ = 20, which is consistent with the analytical result reported in Hurley et al. (2014).

To help reframe the returns to research evidence from past studies, and benchmark future work, we also summarized the projected MIRRs (and their corresponding IRRs) for all 2,208 estimates grouped into various areas of interest (Table 4, see also Tables A3-A5 in the Supplementary Material). We report the projected MIRRs with $T_e$ set to 30 years and $\delta_b = \delta_c$ = 10 percent per year (the central tendency of these parameters in the InSTePP database, see Table 1) and with the estimates grouped by commodity orientation and countries grouped in terms of geographical and economic orientation.

[Table 4: *Reported IRRs and Imputed MIRRs Grouped by Areas of Interest*]

The variation in the mean (and median) of the imputed MIRRs across crops, geographical regions and countries grouped by income class is much more muted than the corresponding variation in the reported IRRs. For example, the mean IRR for the United States is 67.4 percent per year, 22.3 percentage points higher than the corresponding IRR sub-Saharan Africa of 45.1 percent per year. By comparison, the average imputed MIRR for the United States is 17.5 percent per year, just 0.5 percentage points larger than the mean MIRR for sub-Saharan Africa which is 17.0 percent per year. However, some caution is in order when interpreting these differences as Rao et al. (2016) found a complex relationship in the structure of the evidence between developed and developing countries.

### 3.2 Benefit Cost Distributions

We use the following relationship between MIRR and BCR identified by Athanasopoulos and Negrete to derive BCR estimates using imputed MIRRs:

$$MIRR = (1+\delta)\sqrt[Te]{BCR} - 1$$

or equivalently:

$$BCR = \left(\frac{1 + MIRR}{1+\delta}\right)^{Te}$$

The projected BCRs with $T_e$ set to 30 years and $\delta_b = \delta_c = 10$ percent per year are reported in Table 5, with additional projections for $\delta = 5$, 15 and 20 percent per year included in Tables A6 – A8 in the Supplementary Material.

[Table 5: *Imputed BCRs Grouped by Areas of Interest*]

The mean BCR is an incredulous 6,364:1 due to questionable outliers, such as the maximum BCR value of 10 million:1. The median BCR value is a more believable 24.8:1. Such large differences are not apparent in the imputed MIRR evidence. This result reflects the exponential relationship between the *MIRR* and *BCR* with respect to $T_e$ reported above.

## 4. Conclusion

Hurley et al. (2014) questioned the value of using the internal rate of return (IRR) as the key metric for summarizing and assessing the returns to agricultural R&D. They instead recommended the modified internal rate of return (MIRR) or some other metric like the benefit-cost ratio (BCR). Hurley et al. (2016a) showed that the BCR and MIRR produce identical investment rankings when they are calculated with the same discount rate. This is not the case between the IRR and BCR or the IRR and MIRR. The comparisons of project rankings reported here shows that not only do the IRR and MIRR yield substantially different distributions of rates of return, the ranking implied by the two metrics are very different. While these ranking differences shrink when the discount rate used to calculate the MIRR approaches the IRR, the differences remain large when using the magnitude of discount rates that are commonly used in the literature for calculating BCRs. These results raise additional questions about the sensibility of using IRRs as the key metric for evaluating returns to agricultural R&D. The recalibrated returns-to-research results summarized in Tables 4 and 5 (and in Tables A3-A8, in the Supplementary Material) also provide a series of MIRR and BCR distributions by which to benchmark future rates of return to research estimates.

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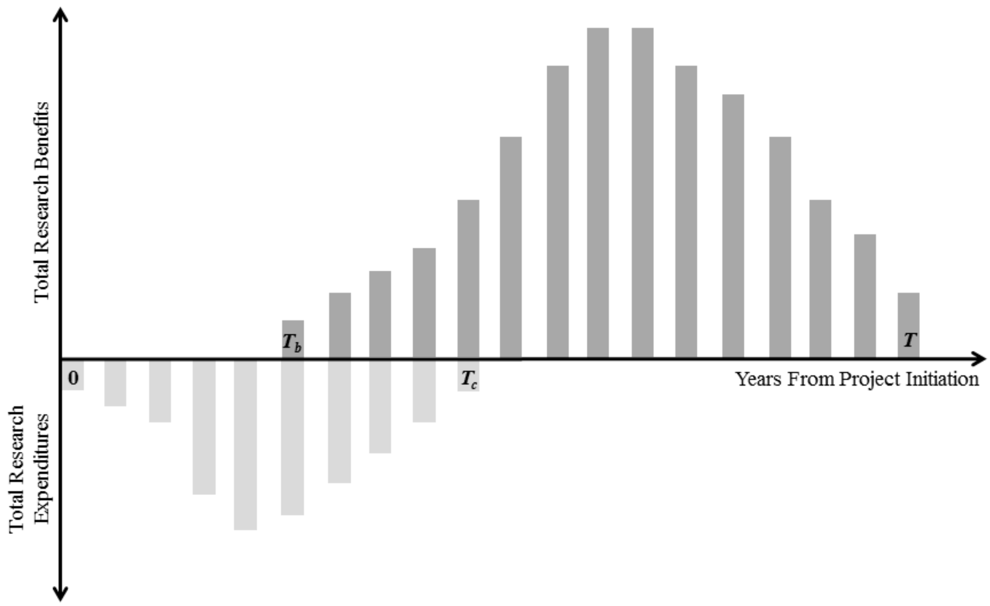
**Figure 1: Illustrative Research Cost and Benefit Streams**




*Source*: Authors construction.

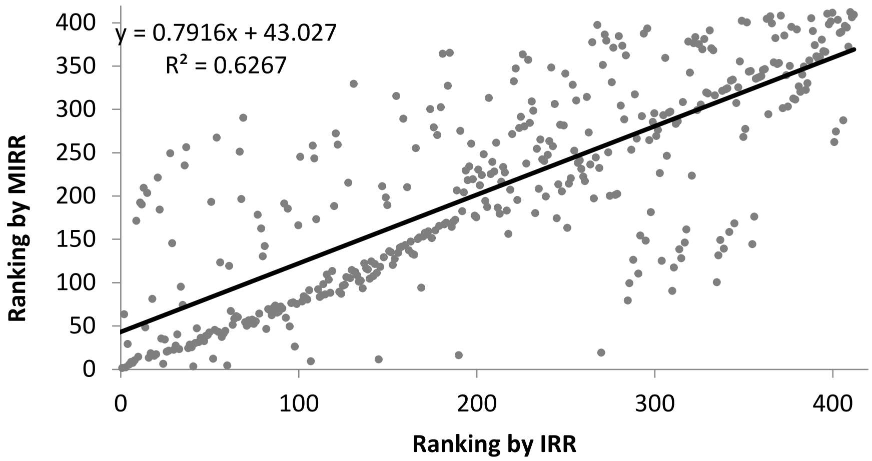
**Table 1: Research Lags, Ts, and Discount Rates, δs, from the Published Evaluations**

| | Sample | Sample size | Mean | s.d. | Min | 25th percentile | Median | 75th percentile | Max |
|---|---|---|---|---|---|---|---|---|---|
| | | | | | | *(years)* | | | |
| Tb | Full | 2,418 | 6.12 | 6.32 | 0 | 1 | 5 | 9 | 49 |
| Tc | Full | 2,418 | 22.72 | 17.43 | 0 | 9 | 21 | 32 | 102 |
| T | Full | 2,418 | 30.77 | 16.70 | 0 | 20 | 27 | 42 | 142 |
| | | | | | | *(percent per year)* | | | |
| □ | Full | 1,161 | 7.88 | 3.33 | 2 | 5 | 9 | 10 | 20 |
| | Reporting IRR | 974 | 8.06 | 3.36 | 2 | 5 | 9.5 | 10 | 20 |
| | Reporting BCR | 747 | 6.9 | 3.27 | 2 | 5 | 5 | 10 | 15 |
| | Reporting IRR & BCR | 560 | 6.89 | 3.35 | 2 | 4 | 5 | 10 | 15 |
| | Reporting nominal ROR | 201 | 9.08 | 2.79 | 3 | 6 | 10 | 10 | 20 |
| | Reporting real ROR | 800 | 7.57 | 3.54 | 2 | 5 | 8 | 10 | 20 |

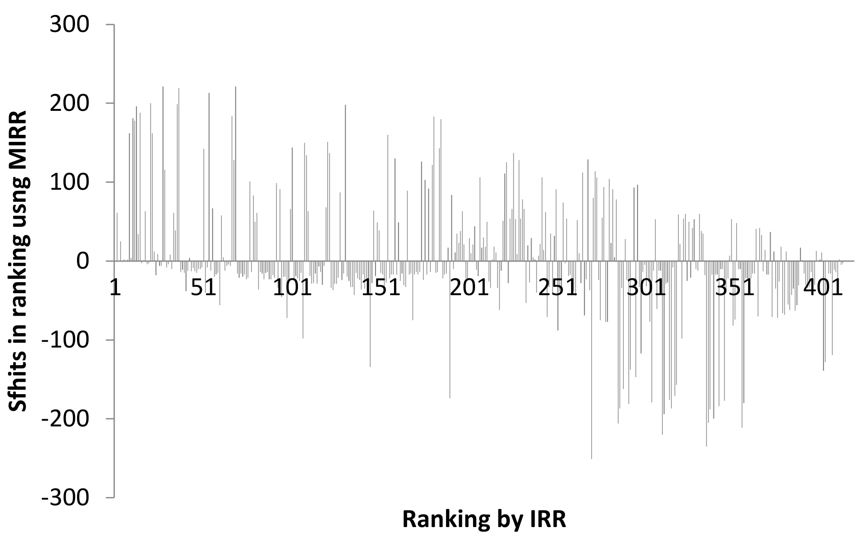
*Source*: Authors construction.

**Figure 2: Reported IRRs versus MIRRs Using the Study's BCRs and *T* for $T_e$**

Panel (a): Scatter plot and ordinary least squares regression results for these rankings.




Panel (b) Difference in rankings arranged according to the IRR rankings.

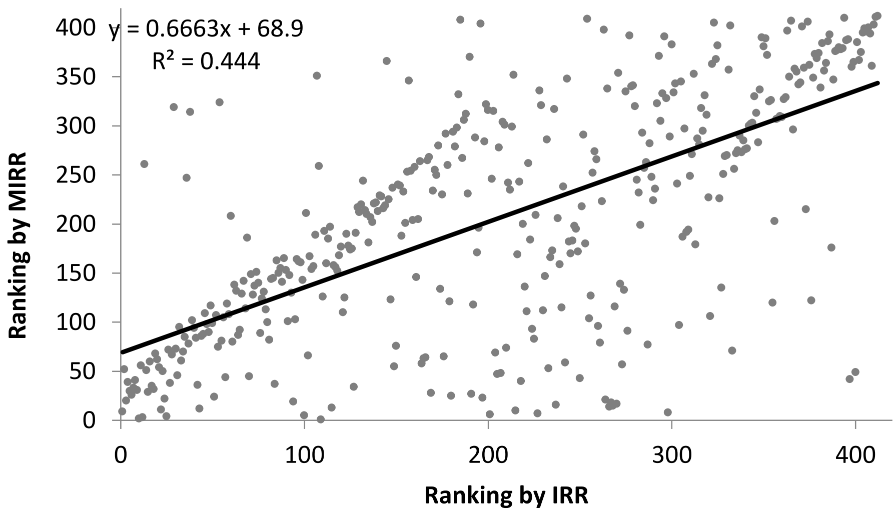



*Source:* Authors construction**.**

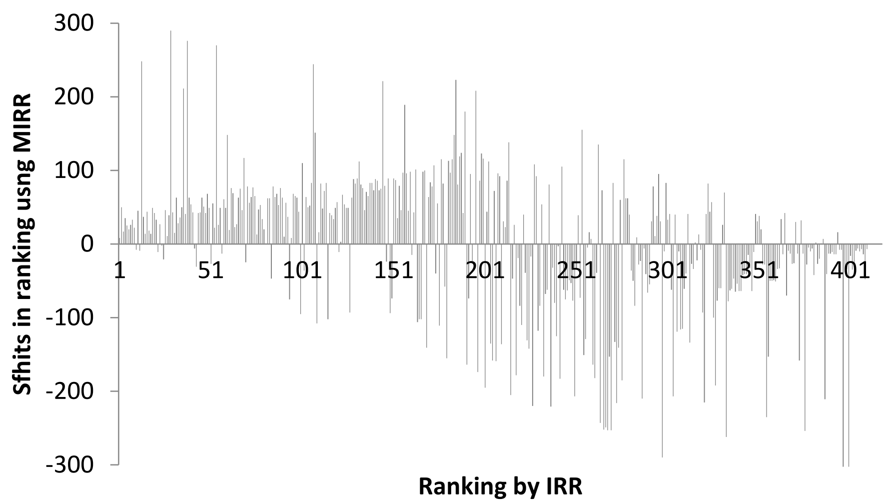
*Notes*: Comparison of IRR and MIRR rankings for the 412 evaluations that reported an IRR and BCR where the MIRR is calculated by transforming the BCR based on the length of the project and discount rate the study used to construct the BCR

**Figure 3: Reported IRRs versus Imputed MIRRs Using $T_e$ of 30 and $\delta$ of 0.05**

Panel (a) Scatter plot and ordinary least squares regression results for these rankings




Panel (b) Difference in rankings arranged according to the IRR rankings

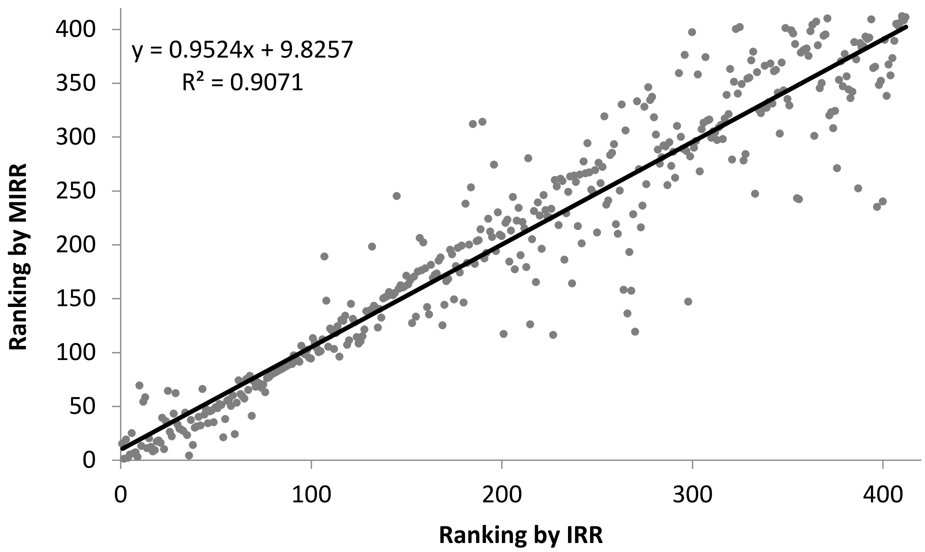



*Source:* Authors construction**.**

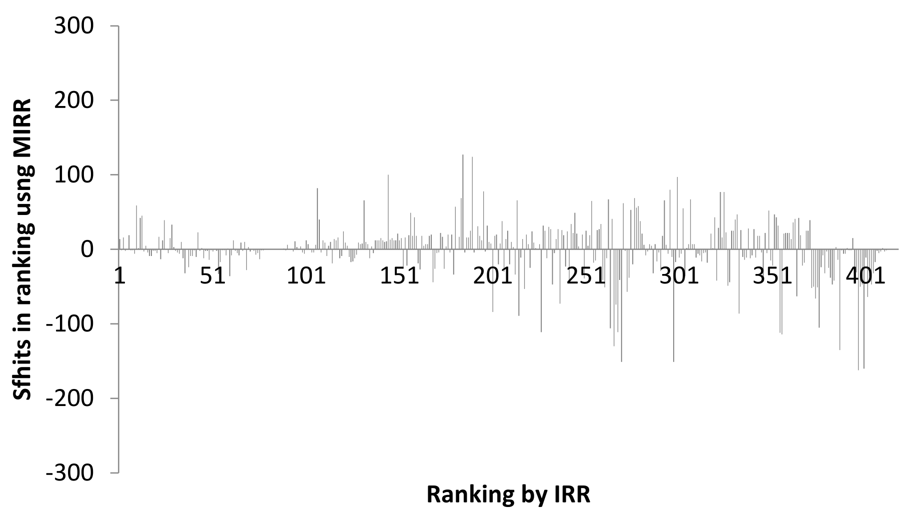
*Notes*: Comparison of IRR and MIRR rankings for the 412 evaluations that reported an IRR and BCR where the MIRR is approximated using a 30 year evaluation period ($T_e$ = 30) and 5 percent discount rate ($\delta$ = 0.05).

**Figure 4: Reported IRRs versus Imputed MIRRs Using $T_e$ of 30 and $\delta$ of 0.2**

Panel (a) Scatter plot and ordinary least squares regression results for these rankings




Panel (b) Difference in rankings arranged according to the IRR rankings




*Source:* Authors construction**.**

*Notes*: Comparison of IRR and MIRR rankings for the 412 evaluations that reported an IRR and BCR where the MIRR is approximated using a 30 year evaluation period ($T_e$ = 30) and 20 percent discount rate ($\delta$ = 0.2).

**Table 2: Regression Results Relating MIRR to IRR**

| ln(MIRR) | $\delta_r = \delta_c$ | | | |
|---|---|---|---|---|
| | **5%** | **10%** | **15%** | **20%** |
| ln(IRR) | 0.348*** | 0.304*** | 0.271*** | 0.249*** |
| | (0.0209) | (0.0142) | (0.0121) | (0.0121) |
| $T$ | 0.00860*** | 0.00290*** | 0.000852** | 0.000191 |
| | (0.000941) | (0.000563) | (0.000410) | (0.000373) |
| $T_b$ | 0.0134*** | 0.0144*** | 0.0109*** | 0.00623*** |
| | (0.00293) | (0.00185) | (0.00146) | (0.00139) |
| $T_c$ | -0.00540*** | -0.00216*** | -0.00102*** | -0.000573* |
| | (0.00105) | (0.000536) | (0.000363) | (0.000308) |
| Intercept | 1.104*** | 1.594*** | 1.959*** | 2.242*** |
| | (0.105) | (0.0661) | (0.0533) | (0.0526) |
| Observations | 412 | 412 | 412 | 412 |
| R-squared | 0.539 | 0.736 | 0.827 | 0.845 |

*Source:* Authors construction**.**

*Notes*: Ordinary least squares regression results relating the MIRR to the IRR, length of time from project initiation that research expenditures were accrued ($T_c$), time from project initiation when research returns began to accrue ($T_b$), and length of time from project initiation when both expenditures and returns ceased to accrue ($T$).

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

**Table 3: Descriptive Statistics, Reported IRRs and Imputed MIRRs**

| **N = 2,208** | **IRR** | **MIRR** | | | |
|---|---|---|---|---|---|
| | | $\boldsymbol{\delta_r = \delta_c}$ **= 5%py** | $\boldsymbol{\delta_r = \delta_c}$ **= 10%py** | $\boldsymbol{\delta_r = \delta_c}$ **= 15%py** | $\boldsymbol{\delta_r = \delta_c}$ **= 20%py** |
| | | (*percent per year*) | | | |
| **Total sample** | | | | | |
| Mean | 63.22 | 14.26 | 17.76 | 21.25 | 24.79 |
| S.D. | 175.64 | 4.96 | 5.26 | 5.43 | 5.63 |
| Minimum | 0.9 | 3.49 | 5.33 | 7.34 | 9.45 |
| **25th percentile** | 23.49 | 11.5 | 14.73 | 17.98 | 21.31 |
| Median | 38 | 13.57 | 16.86 | 20.39 | 23.95 |
| **75th percentile** | 63.75 | 15.94 | 19.97 | 23.78 | 27.5 |
| Maximum | 5,645 | 79.53 | 80.19 | 81.73 | 84.74 |

*Source:* Authors construction**.**

*Notes*: Descriptive statistics for the full sample of IRR estimates and recalibrated MIRR estimates based on the ordinary least squares regression with discount rates equal to 5, 10, 15, and 20 percent, and $T_e$ equal to 30.

**Table 4: Reported IRRs and Imputed MIRRs Grouped by Areas of Interest with $T_e$ = 30 and $\delta$ = 10**

| | MIRR -- Imputed | | | | | | | | IRR -- Reported | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | N | Mean | s.d. | Min | 25th percentile | Median | 75th percentile | Max | Mean | s.d. | Min | 25th percentile | Median | 75th percentile | Max |
| | | | | | | | | *(percent per year)* | | | | | | | |
| All studies | 2,208 | 17.8 | 5.3 | 5.3 | 14.7 | 16.9 | 20.0 | 80.2 | 63.2 | 175.6 | 0.9 | 23.5 | 38.0 | 63.8 | 5,645 |
| Crops | 1,086 | 17.8 | 3.9 | 5.3 | 15.2 | 17.4 | 20.0 | 51.0 | 57.2 | 73.4 | 0.9 | 27.0 | 42.1 | 67.7 | 1,736 |
| Livestock | 205 | 19.6 | 8.0 | 8.7 | 15.8 | 18.5 | 22.0 | 80.2 | 132.1 | 511.8 | 2.5 | 31.0 | 56.0 | 91.4 | 5,645 |
| All agriculture | 747 | 16.7 | 5.1 | 6.8 | 13.7 | 15.5 | 18.2 | 43.1 | 48.9 | 82.5 | 2.0 | 19.1 | 28.1 | 44.1 | 1,219 |
| Natural resources | 29 | 16.5 | 2.8 | 10.5 | 14.6 | 16.6 | 18.9 | 21.4 | 45.3 | 31.2 | 7.0 | 15.8 | 39.0 | 74.4 | 111 |
| U.S. | 842 | 17.5 | 6.6 | 5.5 | 14.2 | 15.9 | 18.9 | 80.2 | 67.4 | 261.7 | 1.3 | 20.8 | 31.9 | 52.0 | 5,645 |
| Other developed country | 356 | 18.6 | 5.1 | 8.7 | 15.1 | 18.2 | 21.6 | 51.0 | 75.8 | 137.6 | 2.5 | 22.0 | 49.0 | 83.7 | 1,736 |
| Asia & Pacific | 249 | 19.6 | 4.3 | 10.4 | 16.9 | 18.7 | 22.0 | 44.2 | 83.3 | 91.6 | 6.0 | 36.2 | 52.0 | 94.3 | 1,000 |
| Latin America & the Caribbean | 367 | 17.0 | 3.0 | 9.8 | 14.8 | 16.6 | 19.0 | 25.9 | 46.3 | 27.9 | 8.0 | 26.6 | 40.0 | 58.0 | 191 |
| Sub-Saharan Africa | 259 | 17.0 | 4.1 | 5.3 | 13.8 | 17.0 | 20.2 | 30.0 | 45.1 | 37.3 | 0.9 | 21.6 | 35.3 | 58.0 | 350 |
| Multinational | 101 | 17.4 | 3.8 | 10.1 | 15.4 | 16.9 | 19.3 | 37.4 | 50.6 | 78.4 | 10.0 | 26.8 | 35.0 | 51.5 | 677 |
| Global | 13 | 17.1 | 2.2 | 12.1 | 16.1 | 17.4 | 18.9 | 19.7 | 44.0 | 23.2 | 10.0 | 26.0 | 48.0 | 52.0 | 84 |
| High income | 1,226 | 17.8 | 6.1 | 5.5 | 14.5 | 16.4 | 20.0 | 80.2 | 69.6 | 229.3 | 1.3 | 21.4 | 34.6 | 62.7 | 5,645 |
| Middle income | 701 | 17.9 | 4.0 | 5.3 | 15.3 | 17.3 | 20.2 | 44.2 | 60.2 | 67.1 | 0.9 | 28.0 | 42.8 | 71.0 | 1,000 |
| Low income | 116 | 16.2 | 3.3 | 7.7 | 14.1 | 15.8 | 18.6 | 25.8 | 38.4 | 26.9 | 3.2 | 22.0 | 33.1 | 48.1 | 188 |

*Source:* Authors construction.

*Notes*: MIRR and IRR numbers are in percentage. The income groups in this table come from the World Bank Analytical Classification for the fiscal year of 2017. Data were accessed from https://datahelpdesk.worldbank.org/knowledgebase/articles/906519 on January 24, 2017. In this study, "middle income" countries include both upper-middle (UM) and lower-middle (LM) income countries from the World Bank classification.

**Table 5: Imputed BCRs Grouped by Areas of Interest with $T_e$ = 30 and $\delta$ = 10**

| | | BCR -- Imputed | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | N | Mean | s.d. | Min | 25th percentile | Median | 75th percentile | Max |
| All studies | 2,208 | 6,364 | 235,048 | 1.1 | 14.3 | 24.8 | 54.49 | 10,863,818 |
| Crops | 1,086 | 108 | 1,656 | 1.1 | 16.1 | 28.7 | 55.48 | 54,008 |
| Livestock | 205 | 66,339 | 770,493 | 2.8 | 18.8 | 37.7 | 89.53 | 10,863,818 |
| All agriculture | 747 | 113 | 617 | 1.7 | 10.9 | 17.5 | 34.53 | 10,804 |
| Natural resources | 29 | 28 | 20 | 4.6 | 13.8 | 23.2 | 41.87 | 77 |
| U.S. | 842 | 16,489 | 380,545 | 1.2 | 12.6 | 19.4 | 41.95 | 10,863,818 |
| Other developed country | 356 | 281 | 2,944 | 2.8 | 15.6 | 35.0 | 82.18 | 54,008 |
| Asia & Pacific | 249 | 142 | 865 | 4.5 | 25.3 | 39.8 | 90.12 | 13,500 |
| Latin America & the Caribbean | 367 | 35 | 32 | 3.8 | 14.6 | 22.9 | 42.42 | 230 |
| Sub-Saharan Africa | 259 | 43 | 57 | 1.1 | 11.3 | 25.9 | 57.67 | 608 |
| Multinational | 101 | 85 | 377 | 4.2 | 16.8 | 24.9 | 46.23 | 3,189 |
| Global | 13 | 30 | 14 | 7.1 | 20.4 | 28.6 | 41.80 | 51 |
| High income | 1,226 | 11,407 | 315,402 | 1.2 | 13.4 | 22.2 | 54.36 | 10,863,818 |
| Middle income | 701 | 78 | 532 | 1.1 | 16.6 | 27.8 | 57.11 | 13,500 |
| Low income | 116 | 29 | 28 | 2.2 | 12.2 | 19.0 | 38.23 | 226 |

*Source:* Authors construction.

## Supplementary Material

### 1. Robustness Considerations: Outlier Diagnostics in Relation to Projecting MIRRs from Reported IRR

Hurley, Rao and Pardey (2016b, Figure 5) reported a wide dispersion in the published rates of return food and agricultural R&D worldwide: ranging from a minimum IRR of -100 percent per year up to 5,645 percent per year (even after setting aside two IRR observations with absurdly large IRRs in excess of half-million percent per year). The presence of extreme or outlier observations for regression analysis can seriously distort the classical ordinary least square (OLS) estimator and lead to unreliable model estimates, which in our instance will be problematic when using regression methods to form MIRR estimates based on reported IRRs.

Rousseeuw and Leroy (1987) categorized outlying observations into three types: vertical outliers, bad leverage points, and good leverage points. Specifically, vertical outliers refer to observations that have outlying values for the corresponding error term but not for the explanatory variables. Good leverage points refer to those with outlying values for the explanatory variables but are located close to the regression line. Bad leverage points refer to observations that have outlying values for the explanatory variables but are located well away from the regression line.

Various robust regression models have been devised to deal with outlying observations. Based upon the concept of a breakdown point, robust regression models explicitly assume that the observations are generated from a mixture of the core data generating process of interest, and a secondary (potentially confounding) process that generates outlier observations. A breakdown point is the number of outliers that can be included in the analysis before it is adversely affected. The higher the value of the breakdown point, the more robust are the model estimates. The OLS estimator admits a breakdown point of zero, thus being non-robust to outliers.

Further the relative efficiency of robust regression estimators can be gauged by comparing them with alternative efficient estimators, such as the maximum likelihood estimator. Therefore, the preferred robust regression estimator is the one that has a high breakdown point while maintaining a satisfactory relative efficiency.

To examine the relationship between the reported IRRs and the projected MIRRs, our first step was to create the scatter plot between the log form of the two variables (Figure A1) while conscious of the possibilities of outliers in terms of other explanatory variables (i.e., *Tb*, *Tc* and *T*). A visual inspection suggests that there are likely good leverage points and vertical outliers, observations that report much lowered MIRRs relative to other observations. Our sample seems little affected by bad leverage points.

[Figure A1: *Scatter Plot of Projected MIRRs and Reported IRRs*]

To identify a preferred estimator, we began with the OLS estimator as our basis of comparison (Table A1, Column 1). We then estimated several variants of the M-estimator—a commonly used robust regression estimator—, which is robust to vertical outliers, but not bad leverage points. More specifically, the least absolute value (LAV) estimator (Table A1, Column 3) focuses on the median rather than the mean errors mute the influence of outliers. However, the LAV estimator suffers from low efficiency, and so the Huber M-estimator (Table A1, Column 4) and the bisquare M-estimator (Table A1, Column 2) were employed as two alternatives with improved efficiency. Although bad leverage points are seemingly absent in our sample,[7] the S-estimator from the second generation of robust regression estimators can be employed to detect their influence. For the purposes of this study, we also deployed an MM-estimator (Table A1, Column 5). By combining an M-estimator with an S-estimator, MM-estimators have high efficiency while preserving a high breakdown point.

[Table A1: *Regression Results Relating MIRR to IRR—OLS and Various Robust Regression Models*]

Comparing among the regression results, the value of the estimated coefficient for the variable IRR (in log form) is similar and statistically significant across all the models. However, the coefficient estimates for other explanatory variables show more appreciable differences (Table A1). To discern how these alternative models performed in terms of projecting MIRRs (in level form), we deployed each model to project 2,208 MIRRs from the corresponding IRRs in the InSTePP return-to-research database. All the models yielded similar results in terms of the mean, median and other descriptive statistics of the projected MIRRs (Table A2). On this basis

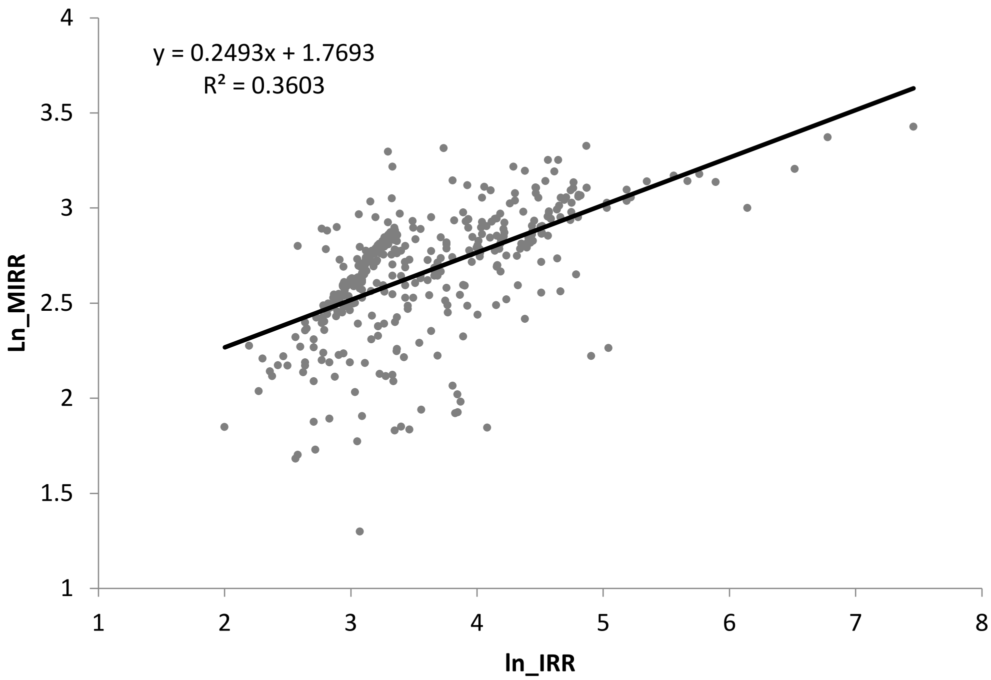
[7] As evidenced by the lack of observations in the lower right part of the figure.

we opted to use the projected MIRRs derived from the OLS regression to characterize the relationship between MIRR and IRR (Figure A2).

[Table A2: *Descriptive Statistics of Projected MIRRs Under Various Models*]

[Figure A2: *Kernel Density Distribution of Projected MIRRs Using OLS*]

**Figure A1: Scatter Plot of Projected MIRRs and Reported IRRs**




*Source:* Authors construction**.**

*Notes*: Discount rate for MIRR estimates set equal to 5 percent.

**Table A1: Regression Results Relating MIRR to IRR—OLS and Various Robust Regression Models**

| | ols | rreg | lav | m | mm85 |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| Ln_IRR | 0.348*** | 0.346*** | 0.341*** | 0.347*** | 0.338*** |
| | (0.0163) | (0.0131) | (0.0158) | (0.0221) | (0.0268) |
| $T$ | 0.00860*** | 0.00727*** | 0.00739*** | 0.00792*** | 0.00677*** |
| | (0.000761) | (0.000614) | (0.000738) | (0.000974) | (0.00109) |
| $T_b$ | 0.0134*** | 0.0108*** | 0.00762** | 0.0116*** | 0.00843*** |
| | (0.00250) | (0.00202) | (0.00243) | (0.00272) | (0.00237) |
| $T_c$ | -0.00540*** | -0.00461*** | -0.00356*** | -0.00480*** | -0.00390*** |
| | (0.000874) | (0.000705) | (0.000848) | (0.000900) | (0.000847) |
| Intercept | 1.104*** | 1.183*** | 1.193*** | 1.146*** | 1.240*** |
| | (0.0766) | (0.0618) | (0.0744) | (0.112) | (0.134) |
| Goodness of fit | 0.54 | 0.64 | 0.37 | 0.63 | 0.74 |
| Observations | 412 | 412 | 412 | 412 | 412 |

*Source:* Authors construction**.**

*Notes*:*ols* refers to the ordinary least square estimator; *rreg* refers to one version of the M-estimator that is based upon Cook's distance and estimated by the Stata command *rreg*; *lav* refers to the least-absolute-value estimator, also known as the quantile regression estimator, and is estimated by the Stata command *qreg*; *m* and *mm85* refer to the M-estimator and MM-estimator, respectively, and both are estimated by the Stata command *robreg* with the corresponding options. The "goodness of fit" statistics are included, but represent a mixture of $R^2$ and pseudo-$R^2$ statistics that are not directly comparable across the models.

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

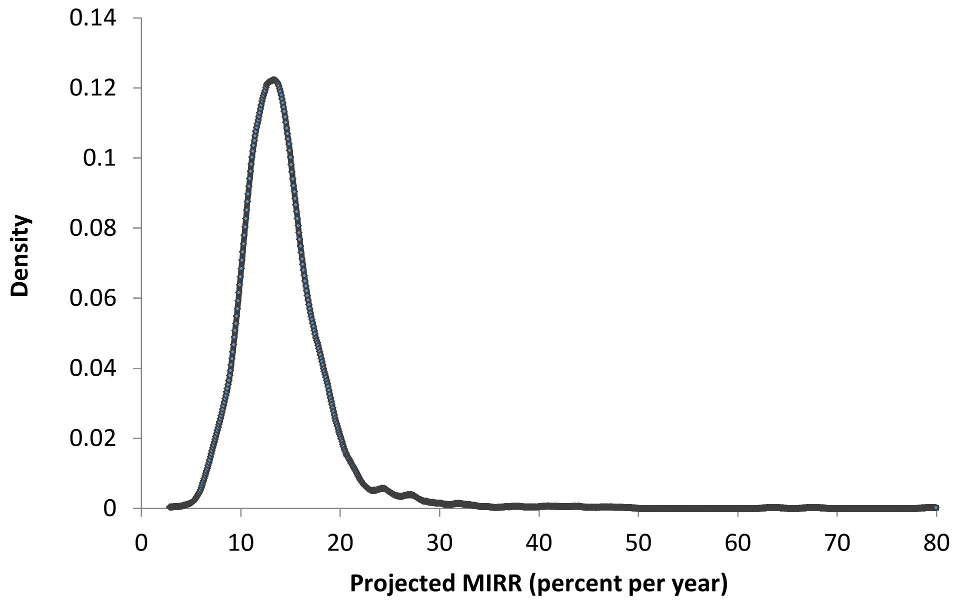
**Table A2: Descriptive Statistics of Projected MIRRs Under Various Models**

| | ols | rreg | lav | m | mm85 |
|---|---|---|---|---|---|
| **Total sample** | 2,208 | 2,208 | 2,208 | 2,208 | 2,208 |
| Mean | 14.26 | 14.69 | 14.68 | 14.52 | 14.85 |
| S.D. | 4.96 | 4.95 | 4.80 | 4.95 | 4.80 |
| Minimum | 3.49 | 3.69 | 3.71 | 3.61 | 3.85 |
| **25th percentile** | 11.50 | 11.97 | 12.00 | 11.78 | 12.19 |
| Median | 13.57 | 13.97 | 13.97 | 13.84 | 14.14 |
| **75th percentile** | 15.94 | 16.45 | 16.40 | 16.23 | 16.62 |
| Maximum | 79.53 | 80.74 | 77.15 | 80.12 | 77.85 |

*Source:* Authors construction**.**

*Notes*: All numbers in percentage.

**Figure A2: Kernel Density Distribution of Projected MIRRs Using OLS**




*Source:* Authors construction**.**

*Notes*: kernel = epanechnikov, bandwidth = 0.6359.

## 2. Tabulation of Projected MIRRs subject to various $T_e$ and $\delta$ values

**Table A3: Projected MIRR with $T_e$ = 30 and $\delta$ = 5%**

| | | MIRR | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | N | Mean | s.d. | Min | 25th percentile | Median | 75th percentile | Max |
| | | | | | *(percent per year)* | | | |
| All studies | 2,208 | 14.3 | 5.0 | 3.5 | 11.5 | 13.6 | 15.9 | 79.5 |
| | | | | | | | | |
| Crops | 1,086 | 14.0 | 3.6 | 3.5 | 11.6 | 13.7 | 15.9 | 48.6 |
| Livestock | 205 | 16.1 | 7.9 | 6.8 | 12.6 | 15.1 | 17.6 | 79.5 |
| All agriculture | 747 | 13.6 | 4.7 | 4.9 | 10.9 | 13.0 | 14.9 | 46.2 |
| Natural resources | 29 | 13.2 | 2.4 | 8.2 | 11.6 | 13.5 | 15.1 | 17.4 |
| | | | | | | | | |
| U.S. | 842 | 14.3 | 6.3 | 3.5 | 11.3 | 13.3 | 15.2 | 79.5 |
| Other developed country | 356 | 15.2 | 4.7 | 6.9 | 11.9 | 14.9 | 17.9 | 48.6 |
| Asia & Pacific | 249 | 15.7 | 4.1 | 7.1 | 13.2 | 15.0 | 17.8 | 43.1 |
| Latin America & the Caribbean | 367 | 13.1 | 2.7 | 6.8 | 11.2 | 12.7 | 15.0 | 21.3 |
| Sub-Saharan Africa | 259 | 13.3 | 3.8 | 3.5 | 10.3 | 13.6 | 16.0 | 25.2 |
| Multinational | 101 | 13.9 | 3.6 | 7.4 | 11.8 | 13.4 | 15.4 | 32.9 |
| Global | 13 | 13.2 | 2.0 | 8.9 | 12.1 | 13.4 | 14.4 | 16.7 |
| | | | | | | | | |
| High income | 1,226 | 14.6 | 5.8 | 3.5 | 11.6 | 13.6 | 16.0 | 79.5 |
| Middle income | 701 | 14.1 | 3.7 | 3.5 | 11.6 | 13.7 | 16.0 | 43.1 |
| Low income | 116 | 12.3 | 3.0 | 5.2 | 10.4 | 11.8 | 14.4 | 20.4 |

*Source:* Authors construction.

**Table A4: Projected MIRR with $T_e$ = 30 and $\delta$ = 15%**

| | | MIRR | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | N | Mean | s.d. | Min | 25th percentile | Median | 75th percentile | Max |
| | | | | | *(percent per year)* | | | |
| All studies | 2,208 | 21.3 | 5.4 | 7.3 | 18.0 | 20.4 | 23.8 | 81.7 |
| | | | | | | | | |
| Crops | 1,086 | 21.5 | 4.2 | 7.3 | 18.8 | 21.1 | 24.0 | 55.3 |
| Livestock | 205 | 23.3 | 8.1 | 10.6 | 19.2 | 22.3 | 25.9 | 81.7 |
| All agriculture | 747 | 19.9 | 5.3 | 8.8 | 16.7 | 18.8 | 21.6 | 48.7 |
| Natural resources | 29 | 19.9 | 3.4 | 13.1 | 16.7 | 19.8 | 23.0 | 25.6 |
| | | | | | | | | |
| U.S. | 842 | 20.7 | 6.6 | 7.7 | 17.2 | 19.3 | 22.6 | 81.7 |
| Other developed country | 356 | 22.2 | 5.5 | 10.6 | 18.2 | 21.7 | 25.4 | 55.3 |
| Asia & Pacific | 249 | 23.5 | 4.6 | 13.3 | 20.4 | 22.4 | 26.0 | 47.9 |
| Latin America & the Caribbean | 367 | 20.7 | 3.2 | 13.0 | 18.4 | 20.1 | 23.0 | 30.8 |
| Sub-Saharan Africa | 259 | 20.5 | 4.4 | 7.3 | 17.4 | 20.8 | 23.8 | 35.1 |
| Multinational | 101 | 20.9 | 4.0 | 13.2 | 18.8 | 20.6 | 22.8 | 42.9 |
| Global | 13 | 20.7 | 2.5 | 15.0 | 19.5 | 20.7 | 22.8 | 23.6 |
| | | | | | | | | |
| High income | 1,226 | 21.2 | 6.3 | 7.7 | 17.5 | 19.9 | 23.6 | 81.7 |
| Middle income | 701 | 21.6 | 4.3 | 7.3 | 19.0 | 20.9 | 24.0 | 47.9 |
| Low income | 116 | 19.8 | 3.6 | 10.4 | 17.6 | 19.5 | 22.3 | 30.6 |

*Source:* Authors construction.

**Table A5: Projected MIRR with $T_e$ = 30 and $\delta$ = 20%**

| | N | MIRR | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | | Mean | s.d. | Min | 25th percentile | Median | 75th percentile | Max |
| | | *(percent per year)* | | | | | | |
| All studies | 2,208 | 24.8 | 5.6 | 9.5 | 21.3 | 24.0 | 27.5 | 84.7 |
| Crops | 1,086 | 25.1 | 4.5 | 9.5 | 22.3 | 24.7 | 28.0 | 60.7 |
| Livestock | 205 | 27.0 | 8.3 | 12.7 | 22.7 | 26.2 | 30.1 | 84.7 |
| All agriculture | 747 | 23.3 | 5.5 | 11.1 | 19.9 | 22.1 | 25.1 | 54.7 |
| Natural resources | 29 | 23.6 | 4.0 | 15.9 | 19.2 | 23.8 | 27.3 | 30.2 |
| U.S. | 842 | 24.1 | 6.6 | 10.1 | 20.4 | 22.9 | 26.1 | 84.7 |
| Other developed country | 356 | 25.8 | 6.1 | 12.7 | 21.3 | 25.5 | 29.2 | 60.7 |
| Asia & Pacific | 249 | 27.3 | 5.0 | 15.8 | 23.9 | 26.1 | 30.1 | 53.0 |
| Latin America & the Caribbean | 367 | 24.4 | 3.4 | 16.4 | 22.0 | 23.8 | 26.6 | 35.5 |
| Sub-Saharan Africa | 259 | 23.9 | 4.7 | 9.5 | 20.6 | 23.9 | 27.3 | 40.5 |
| Multinational | 101 | 24.4 | 4.3 | 16.5 | 22.1 | 23.9 | 26.4 | 48.3 |
| Global | 13 | 24.3 | 3.0 | 17.7 | 22.5 | 24.5 | 26.4 | 28.2 |
| High income | 1,226 | 24.7 | 6.4 | 10.1 | 20.8 | 23.3 | 27.3 | 84.7 |
| Middle income | 701 | 25.3 | 4.7 | 9.5 | 22.4 | 24.6 | 28.1 | 53.0 |
| Low income | 116 | 23.2 | 3.9 | 13.0 | 21.0 | 23.0 | 26.0 | 35.3 |

*Source:* Authors construction.

### 3. Tabulation of Projected BCRs subject to various $T_e$ and $\delta$ values

**Table A6: Projected BCR with $T_e$ = 30 and $\delta$ = 5%**

| | BCR -- Imputed | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | N | Mean | s.d. | Min | 25th percentile | Median | 75th percentile | Max |
| All studies | 2,208 | 5,340 | 209,317 | 0.7 | 6.1 | 10.5 | 19.6 | 9,739,819 |
| | | | | | | | | |
| Crops | 1,086 | 54 | 1,030 | 0.7 | 6.2 | 10.8 | 19.3 | 33,700 |
| Livestock | 205 | 56,535 | 686,356 | 1.7 | 8.1 | 15.8 | 29.9 | 9,739,819 |
| All agriculture | 747 | 68 | 783 | 1.0 | 5.2 | 9.1 | 14.8 | 20,713 |
| Natural resources | 29 | 12 | 7 | 2.4 | 6.3 | 10.3 | 15.8 | 28 |
| | | | | | | | | |
| U.S. | 842 | 13,905 | 338,907 | 0.7 | 5.8 | 9.8 | 16.2 | 9,739,819 |
| Other developed country | 356 | 144 | 1,805 | 1.7 | 6.8 | 14.9 | 32.6 | 33,700 |
| Asia & Pacific | 249 | 74 | 690 | 1.8 | 9.6 | 15.3 | 31.7 | 10,884 |
| Latin America & the Caribbean | 367 | 12 | 11 | 1.7 | 5.6 | 8.4 | 15.4 | 76 |
| Sub-Saharan Africa | 259 | 16 | 21 | 0.7 | 4.4 | 10.5 | 20.0 | 197 |
| Multinational | 101 | 32 | 136 | 2.0 | 6.6 | 10.0 | 16.8 | 1,164 |
| Global | 13 | 11 | 6 | 3.0 | 7.2 | 10.2 | 13.2 | 23 |
| | | | | | | | | |
| High income | 1,226 | 9,592 | 280,883 | 0.7 | 6.2 | 10.5 | 20.0 | 9,739,819 |
| Middle income | 701 | 36 | 413 | 0.7 | 6.2 | 10.8 | 20.0 | 10,884 |
| Low income | 116 | 10 | 9 | 1.1 | 4.5 | 6.6 | 13.0 | 60 |

*Source:* Authors construction.

**Table A7: Projected BCR with $T_e$ = 30 and $\delta$ = 15%**

| | | BCR -- Imputed | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | N | Mean | s.d. | Min | 25th percentile | Median | 75th percentile | Max |
| All studies | 2,208 | 8,694 | 306,008 | 1.9 | 33.0 | 60.6 | 139.1 | 14,036,399 |
| | | | | | | | | |
| Crops | 1,086 | 266 | 3,828 | 1.9 | 40.1 | 71.3 | 147.1 | 124,540 |
| Livestock | 205 | 89,770 | 1,002,820 | 4.7 | 45.2 | 97.0 | 233.4 | 14,036,399 |
| All agriculture | 747 | 279 | 1,685 | 2.9 | 23.6 | 40.2 | 82.0 | 34,071 |
| Natural resources | 29 | 73 | 58 | 9.4 | 23.8 | 52.8 | 115.0 | 217 |
| | | | | | | | | |
| U.S. | 842 | 22,289 | 495,395 | 2.2 | 26.9 | 46.4 | 104.9 | 14,036,399 |
| Other developed country | 356 | 710 | 6,918 | 4.7 | 34.7 | 84.3 | 203.2 | 124,540 |
| Asia & Pacific | 249 | 359 | 1,884 | 9.7 | 60.6 | 98.4 | 236.1 | 28,977 |
| Latin America & the Caribbean | 367 | 90 | 88 | 9.1 | 36.7 | 56.8 | 116.4 | 725 |
| Sub-Saharan Africa | 259 | 108 | 157 | 1.9 | 28.6 | 67.3 | 139.1 | 1,917 |
| Multinational | 101 | 231 | 1,144 | 9.5 | 40.5 | 63.7 | 110.5 | 10,447 |
| Global | 13 | 77 | 39 | 15.4 | 47.9 | 65.2 | 109.2 | 133 |
| | | | | | | | | |
| High income | 1,226 | 15,517 | 410,610 | 2.2 | 28.8 | 53.1 | 132.6 | 14,036,399 |
| Middle income | 701 | 204 | 1,197 | 1.9 | 42.3 | 68.9 | 147.7 | 28,977 |
| Low income | 116 | 75 | 81 | 4.5 | 30.3 | 48.5 | 95.9 | 702 |

*Source:* Authors construction.

**Table A8: Projected BCR with $T_e$ = 30 and $\delta$ = 20%**

| | | BCR -- Imputed | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | N | Mean | s.d. | Min | 25th percentile | Median | 75th percentile | Max |
| All studies | 2,208 | 14,893 | 503,895 | 3.5 | 76.0 | 145.25 | 338.4 | 22,956,082 |
| | | | | | | | | |
| Crops | 1,086 | 723 | 10,826 | 3.5 | 95.9 | 171.91 | 376.2 | 351,799 |
| Livestock | 205 | 152,132 | 1,650,854 | 8.4 | 106.6 | 248.54 | 615.8 | 22,956,082 |
| All agriculture | 747 | 700 | 4,921 | 5.5 | 53.8 | 93.05 | 191.5 | 112,350 |
| Natural resources | 29 | 196 | 173 | 19.4 | 44.7 | 138.95 | 324.4 | 633 |
| | | | | | | | | |
| U.S. | 842 | 37,628 | 815,667 | 4.2 | 61.1 | 112.67 | 240.6 | 22,956,082 |
| Other developed country | 356 | 2,054 | 19,813 | 8.4 | 75.8 | 212.70 | 503.0 | 351,799 |
| Asia & Pacific | 249 | 992 | 5,254 | 19.0 | 144.2 | 244.25 | 622.8 | 80,352 |
| Latin America & the Caribbean | 367 | 227 | 235 | 21.8 | 90.8 | 140.23 | 275.6 | 2,093 |
| Sub-Saharan Africa | 259 | 263 | 459 | 3.5 | 63.3 | 142.49 | 326.0 | 6,163 |
| Multinational | 101 | 633 | 3,412 | 22.6 | 93.2 | 142.42 | 261.7 | 31,731 |
| Global | 13 | 193 | 118 | 31.0 | 101.6 | 166.31 | 258.5 | 402 |
| | | | | | | | | |
| High income | 1,226 | 26,447 | 676,125 | 4.2 | 66.2 | 124.59 | 325.1 | 22,956,082 |
| Middle income | 701 | 552 | 3,373 | 3.5 | 98.8 | 169.71 | 388.7 | 80,352 |
| Low income | 116 | 185 | 227 | 9.0 | 70.6 | 116.32 | 237.1 | 2,017 |

*Source:* Authors construction.