Methods for measuring and monitoring systemic change in the agriculture sector have drawn increased attention in recent years. Good practice dictates that continual data analysis be integrated into management systems to enable evidence-based, adaptive learning. Yet in this data-driven age, practical methods for quantifying local actor investment and performance remain surprisingly underutilized by agricultural development project implementers.

Understanding the sustainability of project impact requires us to measure both “buy-in indicators”, focusing on local actor investment in a project model, and “imitation indicators”, focusing on replication from non-project actors. Fintrac has learned over the past 25 years that the initial success experienced by early adopters – local actors who are first to risk their scarce resources – establishes momentum for continued buy-in and is a prerequisite for broader replication.

To continually measure early adopter performance, Fintrac’s dedicated Monitoring & Evaluation teams utilize a practical tool-kit of statistical analytical methodologies. We collect statistically significant samples of local actor investment and performance, then critically analyze the data to determine if returns on investment are not only anecdotally observable, but representative of the population of project beneficiaries. Where data identifies areas for improvement, or statistical ambiguity, we adapt our implementation tactics, and/or data collection methods to maintain the momentum of local investment beyond the project life cycle.

As a practical example of what this analytical process looks like at the farm-level, we present data from a statistically significant sample of smallholder tomato farmers on the USAID Tanzania Agriculture Productivity Program (TAPP). We first look at the role of traditional metrics, and then explore how basic regression analysis methodologies allow us to delve deeper into the data in an attempt to quantify the statistical relationship between farmer returns and investment in recommended agro-inputs. Below is a summary of descriptive statistics from the sample of tomato farmers (n=339):

### Table 1: Traditional Metrics – Descriptive Statistics

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>Minimum</th>
<th>Maximum</th>
</tr>
</thead>
<tbody>
<tr>
<td>Land size (ha)</td>
<td>.64</td>
<td>1</td>
<td>3</td>
</tr>
<tr>
<td>Production (kg)</td>
<td>9.821</td>
<td>118</td>
<td>16,000</td>
</tr>
<tr>
<td>Gross margin (US$)</td>
<td>$1,389</td>
<td>-$394</td>
<td>$9,200</td>
</tr>
<tr>
<td>Hybrid Seeds (US$)</td>
<td>$44.36</td>
<td>$1</td>
<td>$1,500</td>
</tr>
<tr>
<td>Fertilizer (US$)</td>
<td>$49.24</td>
<td>$0</td>
<td>$450</td>
</tr>
<tr>
<td>Crop Protection (US$)</td>
<td>$48.39</td>
<td>$0</td>
<td>$500</td>
</tr>
</tbody>
</table>

Traditional reporting metrics as illustrated in Table 1, tend to focus on cross-sectional mean returns in terms of volumes, yields, investments, and income compared to baseline data. The mean farm performance following TAPP-facilitated knowledge exchange, according to this sample, points to early adopter success in terms of profitability. The average gross margins of $2,170/ha over a production cycle of approximately 75 days is significantly in excess of traditional smallholder returns and 46% above the baseline of $1,488/ha. The results indicate promising potential for continued farmer buy-in; however, this provides merely a snapshot in time, and does not quantify the role of the package of recommended input technologies toward that performance.

### Regression Analysis – Marginal Farmer Returns

Regression analysis allows us to go further by estimating the statistical relationship between variables of interest. In the example from Tanzania, we can analyze the marginal response of farm performance on farmer input investments. In other words, do we know how much income an early adopter generates from marginal investments in recommended inputs? A linear regression model, using Ordinary Least Squares to provide estimates, can help us begin to answer this question.

First, we design a basic linear regression model to estimate the change in our dependent variable Y (in this case, gross margins) given a change in explanatory variable X (here we use seed, fertilizer and crop protection). The model estimates each coefficient (β) holding all other explanatory variables constant. The model and estimates are presented here:

**Model 1:** \[ Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + u \]

<table>
<thead>
<tr>
<th>Y (Gross Margin)</th>
<th>X (Seed)</th>
<th>( \beta )</th>
<th>p</th>
<th>S.E</th>
<th>95% C.I.</th>
<th>R²</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gross Margin (USD)</td>
<td>X1:Seed</td>
<td>3.74</td>
<td>.000</td>
<td>0.97</td>
<td>(1.82, 5.66)</td>
<td>.122</td>
</tr>
<tr>
<td></td>
<td>X2:Crop Protection</td>
<td>3.22</td>
<td>.077</td>
<td>1.81</td>
<td>(-0.34, 6.79)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>X3:Fertilizer</td>
<td>2.36</td>
<td>.258</td>
<td>2.08</td>
<td>(-1.74, 6.46)</td>
<td></td>
</tr>
</tbody>
</table>

The first important statistic this model presents us is the correlation coefficient (R²). In this case, our model tells us that only about 12% of the variation in tomato income can be explained by the variation in investments of seed, fertilizer, and crop protection products. This number is crucially important. Essentially, it verifies the notion that farm technologies are NOT “magic bullets”. Transformational input technologies must be applied appropriately in tandem with GAPs, and even then, there are numerous off-farm variables such as the enabling environment, seasonality of market prices, geographic proximity to markets, etc. that will influence farmer income.

We then move on to our coefficient estimates (β) to examine the marginal returns on farmer investments in inputs. The estimate for \( \beta_1 \) illustrates the marginal return on farmer investment from improved seed by calculating the covariance between Y and X₁, and suggests that for every dollar a farmer spends on the recommended tomato seed variety, s/he returns an average of $3.74 in gross margins. The near statistical certainty (p = .000) allows us to extrapolate the estimates to the population of project-supported farmers.
Next, we see the estimate of marginal returns from crop protection investments is statistically significant albeit with less certainty. The p-value of .077 for $\beta_2$ indicates that in repeated sampling our estimate is expected to be correct approximately 92% of the time. This allows us to conclude with relatively high confidence that $\$1$ of farmer investment in the recommended crop protection package has returned $\$3.22$ in gross margins.

Finally, our estimate for the marginal return from fertilizer ($\beta_3$) does not allow us to confidently extrapolate data to the population level. We see a standard error (2.08) that is high relative to the coefficient estimate (2.36) leading to an imprecise confidence interval (-1.74, 6.46). Finally, the p-value (p=.258) indicates that in repeated sampling our estimate is not expected to reflect the true population mean at least 25% of the time. Therefore, based on the estimates from this sample, we cannot be statistically certain of farmers' marginal returns in relation to their fertilizer investments.

The statistically significant estimates of farmer investment returns related to seed and crop protection suggest to us that farmer demand for recommended seed varieties and crop protection products may be more likely to be sustained after the project ends. Alternatively, the statistically ambiguous results from the fertilizer data encourage us to dig deeper.

Before we draw any conclusions, it is prudent to re-specify the regression model to try to isolate the causes. One possible strategy is to change the dependent variable and examine the relationship between input investments and productivity to determine if the inputs are generating the on-farm results we would expect. Model 2 accounts for farm size and examines the covariance of productivity with farmer input investments.

Model 2: $Y = \beta_0 + \beta_1X_1 + \beta_2X_2 + \beta_3X_3 + u$

<table>
<thead>
<tr>
<th>$Y$</th>
<th>$X_1$: Seed/ha</th>
<th>$X_2$: Crop Protection/ha</th>
<th>$X_3$: Fertilizer/ha</th>
<th>$\beta$</th>
<th>p</th>
<th>S.E</th>
<th>95% C.I.</th>
<th>$R^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Yield (kg/ha)</td>
<td>75.2</td>
<td>0.002</td>
<td>23.7</td>
<td>(28.5, 121.9)</td>
<td>21.1</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$X_1$: Seed/ha</td>
<td>159.3</td>
<td>0.000</td>
<td>28.6</td>
<td>(103.1, 215.5)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$X_3$: Fertilizer/ha</td>
<td>11.1</td>
<td>-0.757</td>
<td>35.9</td>
<td>(-59.5, 81.77)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

First, we see that Model 2 explains approximately 21% of the variance in productivity ($R^2 = .211$). The increase may reflect the removal of effects of off-farm variables such as market price fluctuations, and accounting for farm size. Nonetheless, with 79% of the variance in productivity left unexplained by the model, we recognize that additional on-farm variables, besides the selected inputs, such as application of GAPs, labor availability, water resource management, climate variations, application of additional agro-inputs, etc. will undoubtedly influence productivity.

Next, statistically significant estimates for $\beta_1$ and $\beta_2$ indicate a marginal return from investments in seed/ha of 75.2 kg/ha, and a marginal return from investments in crop protection/ha of 159.3 kg/ha. However, we are again faced with a statistically uncertain estimate for the relationship between productivity returns and fertilizer investments (p=.757) and therefore cannot infer the estimate for $\beta_3$ on the population of project farmers.

Opportunities for Adaptive Management

Given the statistical uncertainty of the estimate for $\beta_3$ in both Model 1 and Model 2, we are encouraged to further explore the possible reasons for seemingly ambiguous marginal returns from fertilizer. We assume that good soil nutrient management, including farmer investment in and application of appropriate blends of Nitrogen, Phosphorous, and Potassium (NPK) fertilizer would lead to positive farmer returns; so what could explain these counterintuitive estimates?

Where regression analysis does not provide answers, it can raise important questions for adaptive management. Raising questions enables our teams to continually assess realities on the ground. There are numerous avenues to investigate, and a few possibilities for further examination are provided here:

Methodological Questions are examined by our M&E teams to constantly improve data collection, analysis, and interpretation:

1) Outliers? Examine data outliers to understand if those observations exhibit a geographic, demographic, behavioural, or other pattern at the farm-level to be addressed.

2) Data collection? Survey design (recall period vs. records) and interview methods may influence reliability of the data.

3) Model specification? The relationship between variables may be non-linear; a different functional form may be needed.

Farm-level Questions allow us to examine the agronomic, socioeconomic, and/or ecological constraints under which early adopters may be operating:

1) Improper use? Are farmers applying the correct mixtures or volumes of the recommended fertilizers? If not, why not?

2) Good Agricultural Practices? Are farmers applying the full suite of GAPs in tandem with recommended fertilizer package?

3) Water resources? Do farmers have access to water resources to increase the efficacy of water-soluble fertilizers?

If any explanation is determined to be legitimate, then teams adapt their tactics, sample again, and examine the results to determine if our initial hypothesis of factors driving performance held. When working with cross-sectional data it is important to take snapshots at different points in time to understand trends and momentum in the local change process.

Lessons Learned

- Statistically significant farm-level data provide “buy-in” indicators which quantify early adopter performance and the likelihood of their sustained technology adoption.

- Traditional metrics provide an important snapshot, but alone they cannot quantify the statistical relationship between variables. Regression analysis is a practical method to do so.

- Regression analysis does not indicate causality. It estimates correlation and covariance between variables, and highlights questions for further examination, enabling project teams to learn, adapt and maximize early adopter performance.

- Here we use regression for farm-level performance analysis, but the methods presented can also be used to test the relationship between many different market system variables, including factors driving firm-level performance, youth engagement, or the health/agriculture nexus to name a few.
References:


Key Terms:

Coefficient: This is the estimated value of the slope, or the estimated change in the dependent variable, given a marginal increase in the explanatory variable.

Confidence Interval: The 95% confidence interval provides a range that we are 95% confident the true population mean will fall between.

Linear relationship: data may exhibit several relationships, or functional forms. The most straightforward is the linear relationship: \[ Y = a + bX \]. In this case, the relationship between the explanatory variable (X) and the dependent variable (Y) is characterized by a constant slope (ie; a straight line).

Non-linear relationship: It is also possible for data to exhibit other functional forms, such as a quadratic function where \[ Y = a + bX + cX^2 \]. In this case, a relationship is curve-linear where the slope is positive up to a threshold where it then becomes negative. For example, returns from application of inorganic fertilizer or agrochemicals may be positive up to a point where overuse results in declining, or even negative returns.

Ordinary Least Squares: A method of estimating a function which minimizes the distance between the observed data and the estimated parameters of the data.

p-value: The p-value provides the statistical significance of estimates. It is essentially the probability of incorrectly extrapolating the data to the population. Typically, in social sciences research, a p-value greater than .10 is considered unacceptably high; however, researchers are free to establish an acceptable p-value lower or higher based on the accuracy required and/or anticipated consequences of being wrong.

Standard Error: This is the standard deviation of the sample data. The average variance, or dispersion of the observations around the estimated mean. When compared to an estimate, standard error provides an indication of the precision of the estimate.

About the Fintrac University Knowledge & Learning Brief Series:

Fintrac University is an e-learning platform designed to build Fintrac’s global staff capacity in agricultural development practices, strategies, and processes. The Knowledge & Learning Brief Series was created for Fintrac University as a set of evidence-based analyses examining the efficacy and local sustainability of the Fintrac methodology across various development contexts. Each paper highlights a particular project component or approach within or across countries, and examines whether the data validates our goal of sustainable impact for smallholder farming families. As part of our commitment to external as well as internal learning, we are making these papers available to the wider international agricultural development community to share lessons learned from our field programs and contribute to the vital discussion around how best to achieve the goal of locally-led poverty reduction.

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