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### **A Quantile Regression Analysis of Micro-lending's Poverty Impact**

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### Abstract

This paper aims to evaluate the impact of a microlending program on ameliorating measured poverty within its client population, with the aim of improving that impact. We analyze over 18,000 women micro-finance clients of the Negros Women for Tomorrow Foundation (NWTF), a database using the Progress out of Poverty (PPI) Scorecard as a measure of poverty. Analysis using both OLS and quantile multivariate regression models shows how observable borrower attributes affect the ability of clients to reduce their measured poverty. Loan size, duration, and the economic activity supported all have strongly identifiable effects. Moreover, estimates suggest which among the poor are receiving the greatest effective help by the program. Results offer specific advice to the NWTF and other micro-lenders: impact is greatest with fewer, larger loans in particular economic sectors (sari-sari, service and trade) but require patience as each additional year increases the client's average change in poverty score.

**Keywords:** micro-finance, Grameen, poverty, quantile regression

**JEL codes:** O16, I32, I38, G21

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### Introduction

By one definition, the mean of the national poverty lines for the 10 poorest countries in the world or \$1.25/day (2005 USD adjusted to purchasing power parity), the World Bank estimates that there are 1.4 billion people living under the poverty line (Chen and Ravallion, 2008). That represents a significant drop over the last twenty years, some due to policy and some due to concerted private action. Among private anti-poverty programs, none has become more publicized in recent years than micro-finance, or financial services targeting low-income clients.

Pioneered by Professor Muhammad Yunus in 1983, the Grameen Bank that he started sparked the micro-finance movement which now counts \$25 billion at work in loans worldwide (Dieckmann, 2007). Despite lending to the poorest people in the world (who therefore do

not possess collateral), excellent repayment rates on the order of 95%, have been seen by micro-finance institutions (MFIs) throughout the developing world (Morduch and Haley, 2001). It has thus an appeal to many in the developed world, as a private and even market-based alternative to official foreign aid.

Given the proliferation of micro-finance institutions, this work contributes to the evaluation of impact. Until recently most MFIs spent very little money and effort on impact assessment, preferring instead to allocate resources towards their mission goals (Morduch and Haley, 2001). Naturally, previous research has also faced data limitations, highlighting the need for more research with comprehensive data sets, so this paper uses a proprietary dataset of the Grameen Foundation, containing unique poverty movement data on over 60,000 participants from forty-one branches of the Negros Women for Tomorrow Foundation

(NWTF, a Philippine partner to the Grameen Foundation). Our goal is clear: to evaluate whether microlending has had a positive impact on poverty alleviation and to identify which clients have been most effective in climbing out of poverty. With those results in hand, NWTF and other microlending institutions will be able to make more efficient choices about their resource allocation, to maximize impact for the same cost.

The following section reviews the literature that documents the considerable disagreement about the effects of micro-finance among researchers. Section 3 presents and describes the unique dataset. The fourth section reports regression results, while the final section concludes with specific policy and research recommendations.

### **Literature review**

Traditional financial institutions typically do not extend financial services to the poor, who have a high risk of default, no collateral and high transactions costs. Village moneylenders have traditionally filled this niche, often charging usurious rates because there is little competition (Bottomley, 1975). Stiglitz and Weiss (1981) modeled this situation, where banks are price-setters in the loan market, and due to incomplete information do not charge interest rates on a floating scale according to willingness to pay, instead providing only a few rates. The result is a situation of adverse selection, where the borrower pool is directly determined by the interest rate charged, yet the risk of default increases for low-risk borrowers. Equilibrium interest rates, where credit supplied equals credit demanded, occurs above the interest rate at which returns are maximized, so interest rate ceilings imposed on lending institutions are lower than equilibrium rates, causing market segmentation in which the poorest demanders of credit are excluded.

Tschach (2000) highlighted the importance of transaction costs in the Stiglitz-Weiss model, an assumption which in the original model made large loans, rather than small loans, more profitable to banks. Guttman (2008) provides a clear explanation of how the work of Ghatak (1999), van Tassell (1999), Laffont and N'Guessan (2000), and Ghatak and Guinnane

(2001) elaborated on that amendment, using group lending as a low-cost potential solution to all three: adverse selection, moral hazard, and enforcement.

In typical group liability lending schemes, borrowers sort themselves into a group to apply for their loans, where the group is jointly liable for the totality of the loans to the group, taking advantage of the fact that borrowers are from tightly knit villages and so have better information than lenders have. Thus, by allowing borrowers to form their own groups, borrowers will sort themselves into groups of high and low-risk borrowers. This result is known as positive assortative matching in the micro-finance literature (see, for example, Guttman 2007).

Further, Besley and Coate (1995) found empirical evidence that group members apply social penalties and that if they are severe enough, loan repayment rates in group lending structures exceed individual repayment rates. Thus, the enforcement challenge can also be overcome by micro-finance.

Empirical work has also attempted to measure the impact of micro-finance on poverty. Hulme and Mosley (1998) use data from thirteen different MFIs, concluding that gains are larger for non-poor borrowers. Some of those results may have been due to branch placement bias, and reporting inaccuracy of the data (since clients were asked to report on past years' income). However, Wright (2000) confirms the result that the poorest clients are helped only by MFIs with specific mechanisms which target the poorest.

In contrast, many studies have found positive and sustained benefits from micro-finance. Khandker (2001) finds evidence for a reduction in poverty using panel data analysis. In that study, micro-finance participants fare significantly better than non-participants in per capita income, per capita expenditure, and household net worth. It is possible that this result is due to factors such as adverse selection, but Morduch and Haley (2001) find supporting evidence that micro-finance has had positive impacts on six out of eight Millennium Development Goals: eradicating extreme

poverty and hunger, achieving universal primary education, promoting gender equality and empowering women, reducing child mortality, improving maternal health, and combating HIV/AIDS, malaria and other diseases.

Pitt and Khandker (1998) represent an impact assessment of micro-loans and supports the targeting of women in micro-finance programs. They found that program credit has a larger effect on the behavior of poor households in Bangladesh when women are the program participants, increasing household consumption expenditure 63.6% more than similar micro-loans to men. The study found that men spend a greater percentage of their loans on personal consumption expenditures (such as entertainment, alcohol, etc), while women spend more on schooling, household expenditures, and assets (investments) than their male counterparts. Furthermore, sociological and anthropological studies of micro-finance have found that extending microcredit to women increases women's rights, increases educational attainment, and empowers women. Cheston (2002) concludes that there is significant evidence that micro-finance improves many indicators of women's rights and well-being.

A survey of the empirical literature on the determinants of repayment reveals inconclusive and contrasting results. Four notable studies (Guttman et al. 1997; Zeller 1998; Godquin 2002; Ahlin and Townsend 2003) find contrasting signs for the explanatory variables of loan size, group size, share of irrigated land, and education. Only outside credit opportunities and group cohesiveness have signs which are consistent across the studies. Outside credit opportunities have a negative impact in three studies and are not included in the fourth. Group cohesiveness has a positive impact in two studies has limited significance in the other two. In short, the determinants of repayment performance are not yet generally agreed upon. This paper hopes to bring new evidence to this literature, clarifying the preceding results with

new data and new analytical tools.

## **Data**

The data used in this paper are proprietary information of the Grameen Foundation, information on the clients of the partner organization Negros Women for Tomorrow Foundation (NWTF) in the Philippines. Fieldworkers collected easily observable and verified data on client borrowers from 2002 through 2008.

As the dependent variable, a measure of poverty, fieldworkers for the NWTF interviewed each borrower in order to calculate a poverty score (pscore), calculating that value when a client joins the NWTF, and recalculating it when a borrower pays back his/her loan (lscore). Scores are computed using the Progress out of Poverty Index (PPI), a simple tool endorsed by the Consultative Group to Assist the Poor (CGAP), the Grameen Foundation and the Ford Foundation that estimates the likelihood that clients fall below the national poverty line. While built on a universal methodology, each PPI is country-specific and questions used by NWTF were based on the best available nationally representative income and expenditure household survey (Grameen, 2009). Table 1 is the complete scorecard used for every client in our sample. Notice that it requires simple answers and minimal calculation.

PPI poverty scores (and corresponding poverty likelihoods) are determined by ownership of particular household assets, number of children, and presence of salaried employment. The theory is that if a client pays back the loan in full, then changes in household assets accurately correlate with changes in poverty level. However, wealth accumulated in other forms (e.g. education and health status of family members) is too difficult to record in a short interview, so is omitted from the score. The poverty score or PPI is the sum of all points calculated on the scorecard.

**Table-1:** Measure of poverty, the Progress out of Poverty Index

Question	Answer	Points
1. How many household members are aged 0 to 17?	>5 3 or 4 1 or 2 0	0 7 16 27
2. Does the family own a gas stove or gas range?	No Yes	0 13
3. How many television sets does the family own?	0 1 >1	0 9 18
4. What are the house's outer walls made of?	Light material (cogom, nipa or sawal, bamboo, anahaw) Strong material (iron, aluminum, tile, concrete, brick, stone, asbestos)	0 2
5. How many radios does the family own?	0 1 >1	0 3 10
6. Does the family own a sala set (living room furniture)?	No Yes	0 9
7. What is the house's roof made of?	Light material (salvaged, makeshift, cogom, nipa or anahaw) Strong material (iron, aluminum, tile, concrete, brick, stone, asbestos)	0 2
8. What kind of toilet facility does the family have?	None, open pit, closed pit, other Water scaled	0 3
9. Do all children in the family have salaried employment?	No Yes No children ages 6-11	0 4 6
10. Do any family members have salaried employment?	No Yes	0 6

The PPI Scorecard is the Grameen Foundation's best poverty measurement tool, but it naturally has limitations. The scorecard has trouble comparing poverty levels among the upper pscore values: it is extremely difficult to progress from a pscore of 95 because to do so one must improve on the one question that did not initially grant full points and no amount of wealth accumulation can push a score beyond 100.

Similarly, there is also a floor on the scorecard of zero. A client who loses everything can only record a zero, and no lower. This is not a purely theoretical case, as one client in the dataset lost 95% of their pscore during their loan period, falling from a pscore of 99 to 4.

Furthermore, the scorecard quite dramatically

advantages a woman with fewer children, regardless of the reason or ability to care for those children. If a client has three children ages 0 to 17, the highest possible pscore is 80. Yet if all three of those children die, even from malnutrition, the client's score will rise 20 additional points.

Given available resources, the survey provides a simple and useful tool for measuring some aspects of poverty. As long as the limitations are made explicit, analysis using it as a base should bear no inherent biases (or at worst, biases no worse than other surveys using self-reported income measures).

The final dataset contains 12656 observations of client records with all variables recorded. It

was necessary to exclude, for example, 13814 additional observations for whom no pre-loan poverty score was available. An additional 13559 client records were unusable because the loan periods were entered inaccurately, suggesting a negative loan duration. Fortunately, the remaining data are error-free and do not appear to represent a biased sample of the whole potential set. Summary statistics of the variables used are presented in Table 2.

The average poverty score rose modestly from 37.21 to 38.72, but the variation across clients is very large (not shown here, but ranging from +88 to -95). On average, clients of the NWTF are becoming roughly four percent ‘wealthier’, but the analysis below asks whether there are predictors or determinants of success which NWTF may leverage into even greater rises for their clients.

**Table-2:** Summary statistics of variables

Variable	Mean	Std. Deviation	Min	Max
Lscore	38.72	19.59	0	99
Pscore	37.21	19.91	0	100
Loan amount	11337.08	6710.19	1000	150000
Number of startup businesses	0.09	0.33	0	4
Number of existing businesses	1.26	0.68	0	6
Years client has been a member of the NWTF	2.81	1.89	2.7x10 <sup>-3</sup>	8.63
Number of loans	6.46	3.88	2	20
	Number of zeroes		Min	Max
Sari-sari sector	8239		0	1
Retail sector	8755		0	1
Agriculture sector	10901		0	1
Fishing sector	10914		0	1
Manufacturing sector	12234		0	1
Processing sector	12060		0	1
Trading sector	9117		0	1
Service sector	11633		0	1

Loans averaged 11337 pesos (roughly \$225 US), and all but five percent of clients were offered loans of less than 20000 pesos (roughly \$400 US). There is reason to suspect that a few clients with larger loans fared significantly differently than the traditional borrower: among clients who received large loans (defined arbitrarily as 20000 pesos or more), the average score improved by almost three times as much as for clients with smaller loans. For that reason we include loan amount as a potential explanatory variable, but also separate out recipients of large loans for their own analysis in the next section.

Most clients used their loans to support an existing business, but some started new businesses (one of them starting four). The

average client has been a member of the NWTF for just under three years , however that period varied from a maximum of over eight and half years to a minimum of a single day. The average client took more than six separate loans, but some clients returned twenty times.

Finally, dummy variables indicate the sector in which economic activity took place during the loan. For many clients, activity was mixed between sectors and the dummy variables reflect that mixture.

### Model and Results

Since the primary goal of the NWTF program is to reduce poverty, we propose a reduced-form model that places that goal, measured as the

recent change in score or ( $lscore - pscore$ ), as the dependent variable. Explanatory variables are motivated by the literature but are naturally also constrained by the dataset. The model uses a linear form, following the literature in leaving all nonlinearities as second-order effects in the error term. However, it improves upon the literature by estimating using a quantile regression, thereby permitting each percentile of the data to speak independently.

### **Our simple reduced-form model is**

*Change in poverty = $f$ (loan size, initial poverty level, sector of activity, business experience of client, duration of loan, loan experience of client)* (1)

### **And we implement this model using variables collected by NWT**

$$\Delta pscore = lscore - pscore = \beta_0 + \beta_1 \log(\text{loan amount}) + \beta_2 pscore + \beta_3 pscore^2 + \beta_4 \text{sector}_i + \beta_{12}(\text{number of startups}) + \beta_{13}(\text{number of existing}) + \beta_{14}(\text{years}) + \beta_{15}(\text{number of loans}) + u \quad (2)$$

Clearly, the error term will subsume a range of unmeasurable characteristics, varying from idiosyncratic economic/financial shocks to personal ability.

In estimation, the Breusch-Pagan test indicates a strong possibility of heteroskedasticity, so all variances are White-corrected in the results which follow. Pairwise correlations between variables are all sufficiently small to minimize concerns about potential multicollinearity. We test for higher-order nonlinear effects of duration (years) but find no change in the significance or values of our coefficients.

The first column of Table 3 presents the OLS results for all loans, while Figure 1 summarizes the OLS results in comparison to the quantile results for each variable. In Figure 1, the horizontal lines indicate the OLS estimate and 95 percent confidence interval, while the irregular line indicates the quantile estimates with a shaded region as the 95 percent confidence interval surrounding it. Quantile regression estimates the same linear model at each percentile of the data distribution, to

explore whether the model might fit differently for clients at different points in the population. As one hundred sets of coefficient estimates would be tedious to read, we display their values in Figure 1 against their OLS counterparts. Notice that whereas the OLS results have a single value for each variable (the estimated coefficient), the quantile results vary nonlinearly across the distribution.

Larger loans are unambiguously associated with larger improvements in poverty score. That result is true at all percentiles, but is particularly powerful near the top percentiles. On average, a 100% change in loan amount (associated here in logarithmic form as a one point increase in the variable) is associated with a 1.59 point change in poverty score. This result accords with Ahlin and Townsend (2003) and Godquin (2002), both of whom found the effect of loan size to be positive.

Initial poverty scores have a nonlinear effect, an effect which is difficult to discern in Figure 1, so Figure 2 summarizes those effects into a net effect of initial poverty (pscore) at every fifth percentile. The net effect is universally negative (greater poverty score reduces the chance of large improvements), a result which is supported by Cho et al. (2008), who conclude that initial poverty measures are negatively correlated with poverty movement. Both the OLS results and quantile results conclude that under the NWT program, clients with the lowest initial poverty scores are helped more by the program than is true of their peers who start at a less disadvantaged position.

Using the OLS results, the nonlinear effect of pscore affects clients with low pscores minimally. Clients with an initial pscore of 5 feel a net effect of that starting position depressing their eventual score change an average of 3 points. In contrast, clients who begin with a pscore of 70 find their change depressed by 39 points on average. The result appears to compress poverty scores toward the mean, but this artifice of the estimation method is the reason to implement quantile analysis.

**Table-3:** OLS results for all loans and large loans

<b>Variable</b>	<b>All loans</b>		<b>Large loans only</b>	
	<b>Coefficient</b>	<b>t-stat</b>	<b>Coefficient</b>	<b>t-stat</b>
Loan amount	1.59	(5.58)***	9.34	(3.92)***
Pscore	-0.60	(20.45)***	-0.76	(5.84)***
Pscore <sup>2</sup>	$5.7 \times 10^{-4}$	(1.60)	$2.3 \times 10^{-3}$	(1.76)*
Number of startup businesses	-0.46	(0.90)	-0.25	(0.11)
Number of existing businesses	0.82	(2.11)**	1.30	(0.97)
Years as a member of the NWTF	0.21	(1.84)*	-0.41	(0.75)
Number of loans	0.69	(11.98)***	0.78	(3.25)***
Sari-sari sector	3.54	(7.32)***	4.05	(2.30)**
Retail sector	2.25	(4.53)***	0.54	(0.28)
Agriculture sector	-0.45	(0.81)	0.11	(0.05)
Fishing sector	0.89	(1.62)	-1.74	(0.79)
Manufacturing sector	0.70	(0.78)	-0.45	(0.16)
Processing sector	2.16	(2.78)**	-3.17	(1.33)
Trading sector	2.03	(4.02)***	-1.10	(0.58)
Service sector	3.19	(5.18)***	-1.24	(0.53)

T-statistics are in parentheses. Significance is indicated as \* for ten percent, \*\* for five percent and \*\*\* for one percent confidence levels.

The quantile results show that initial pscore has a positive linear but negative nonlinear effect at low quantiles, a pattern reversed for higher quantiles. The net effect is difficult to entangle without some calculation, so we present Figure 2 with the average pscore by quantile (in the positive range of the vertical axis) along with the net effect of the linear and nonlinear coefficients on those pscores (in the negative range of the vertical axis). For completeness, the estimated net effects are presented with a confidence range of one standard deviation.

Interestingly, initial pscore seems to have almost precisely the same deleterious effect on progress for roughly three-quarters of the sample. The only subset for which it differs is in the lowest quarter of the quantile distribution, precisely where initial pscore is highest. In other words, it is paradoxically the least poor clients (those with highest initial pscores) who are most hindered by their starting point. This is presumably at least in part due to the one-sided risk facing all clients: if a worst-case scenario of total loss faces two individuals, the potential drop in score is greater for the client with a higher initial score. Still, it presents a powerful piece of evidence that the ultra-poor

are at no disadvantage in their climb out of poverty under the NWTF program than are their less impoverished peers. In a sense, the poorest clients of the NWTF are helped the most, all else equal. There are some obvious differences between economic sectors, with clients who pursue activity in the sari-sari, service and trade sectors improving their poverty scores markedly more than their peers in the agricultural, manufacturing/production or fishing sectors.

Economically, the coefficients are large enough to warrant serious consideration of lending policies. A client who opens a sari-sari store is expected to gain an average of 3.54 poverty score points, versus a borrower using a loan of equivalent size in agriculture is expected to lose 0.45 poverty score points, *ceteris paribus*. The difference is significant statistically and economically, offering clear advice for lenders who are budget constrained but aim to raise poverty scores by the maximum amount.

Clients investing in existing businesses enjoy markedly better outcomes on average than clients who invest in startup businesses, an effect made even more pronounced for those

who invest in multiple startup businesses. Again, perhaps this could serve as policy advice for field agents and loan officers. Improvements come with time and experience, as the coefficients on the variable ‘years as a client of the NWTF’ indicate. Each additional year with the NWTF increases the expected change in poverty score by 0.21 points. Thus, the length of the client-MFI relationship has a positive effect on poverty movement. Notice that this is not a measure of the duration of the loan, or a measure of the time between measurement of pre-loan and post-loan scores, but rather an overall measure of the years that the client has had a relationship with Grameen. More experienced clients are more successful, regardless of the duration of the specific current loan. Work by Tsachach (2000) agrees with this result.

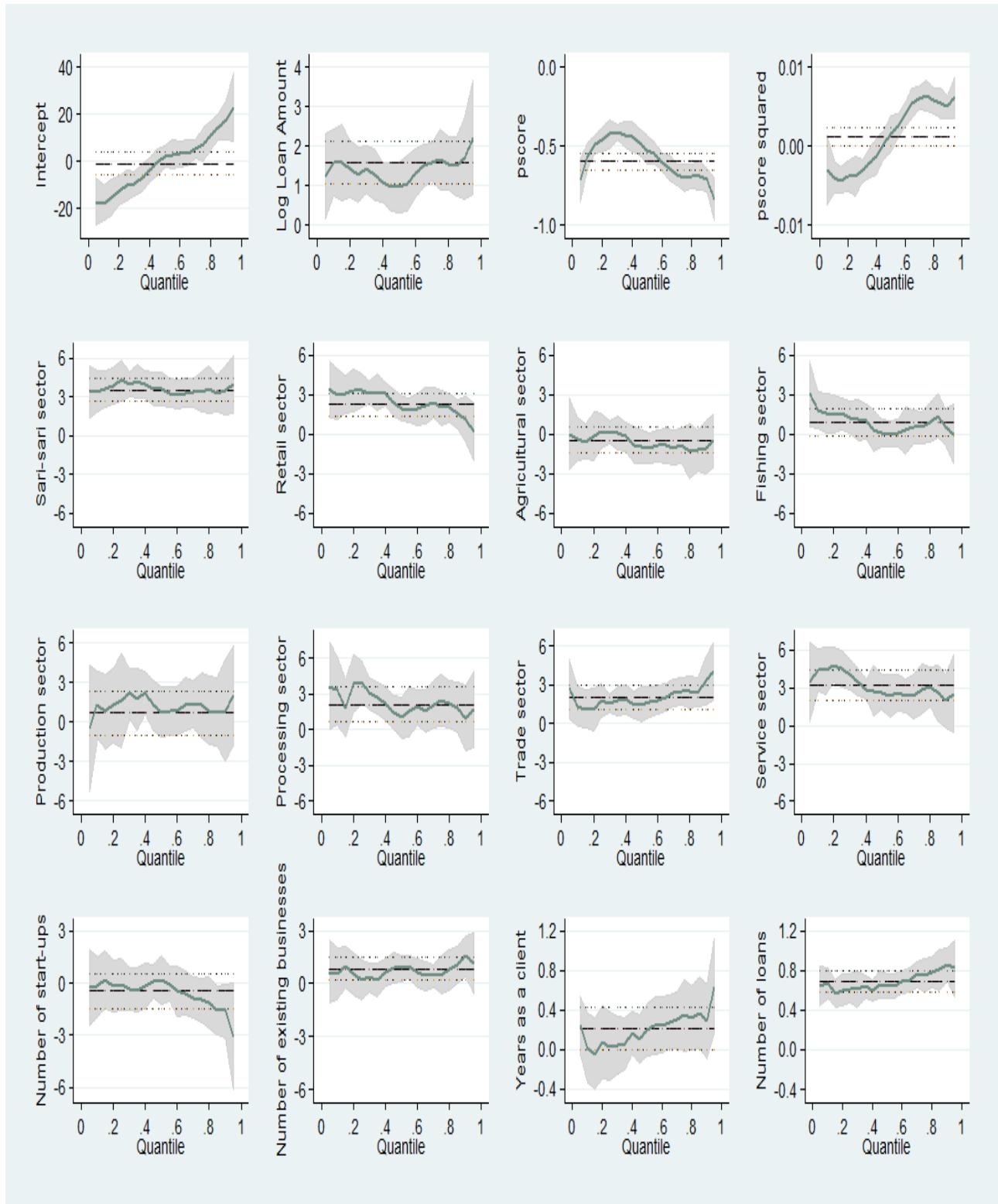
Finally, success is incremental, evidenced by the positive coefficients on the number of loans completed by each client - each additional loan is expected to increase a client's poverty score by 0.69 points. This intuition is already built into the philosophy of Grameen and NWTF, but the evidence is comforting support for the conclusion that repeat clients are progressing out of poverty rather than being pulled into a disabling dependency upon loans as under some possible usurious conditions.

Given that larger loans have larger positive impacts on scores, it is instructive to consider the subset of data that represents only large (20000 pesos or more) loans. As a small and

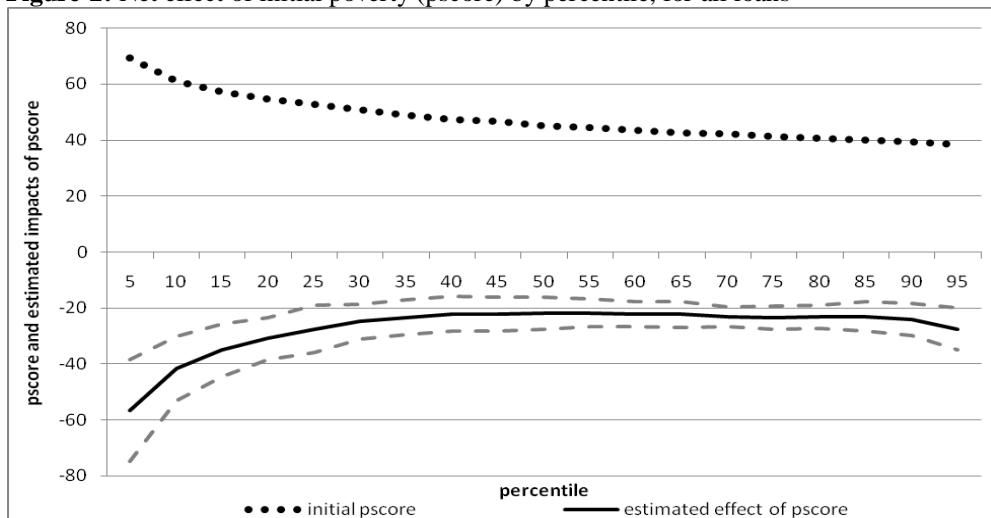
non-random subset, it is unsurprising that many of the effects apparent in the general analysis above differ here. OLS estimates are presented in the final columns of Table 3 above, while Figure 3 below presents quantile estimates.

The size of the loan matters even more at this level of loan, and is always much more positively associated with score improvement than it is for smaller loans. Initial poverty score has a negative impact on progress as for all loans, and the highest scores (or least poor clients) have the greatest disadvantage, a result that parallels the result for all loans above. However, differences in outcomes between members of this ‘large loan group’ matter much less, as the rather flat quantile graphs suggest. Differences between economic sectors are more pronounced, presumably because of a small sample of actors in each activity which thereby make the returns to each activity more risky in the aggregate than is true in the larger sample. Sector-specific coefficients are almost universally insignificant, although the sari-sari sector again stands out significantly more successful in reducing poverty scores. Investments in existing businesses result in an average 1.30 point increase in poverty scores, while startups are riskier (and therefore less predictable and statistically less distinguishable from “no effect” on average). Duration of time spent as a client did not show significance here, although like the pool of all loans, repeated loans had a strong positive effect on poverty scores.

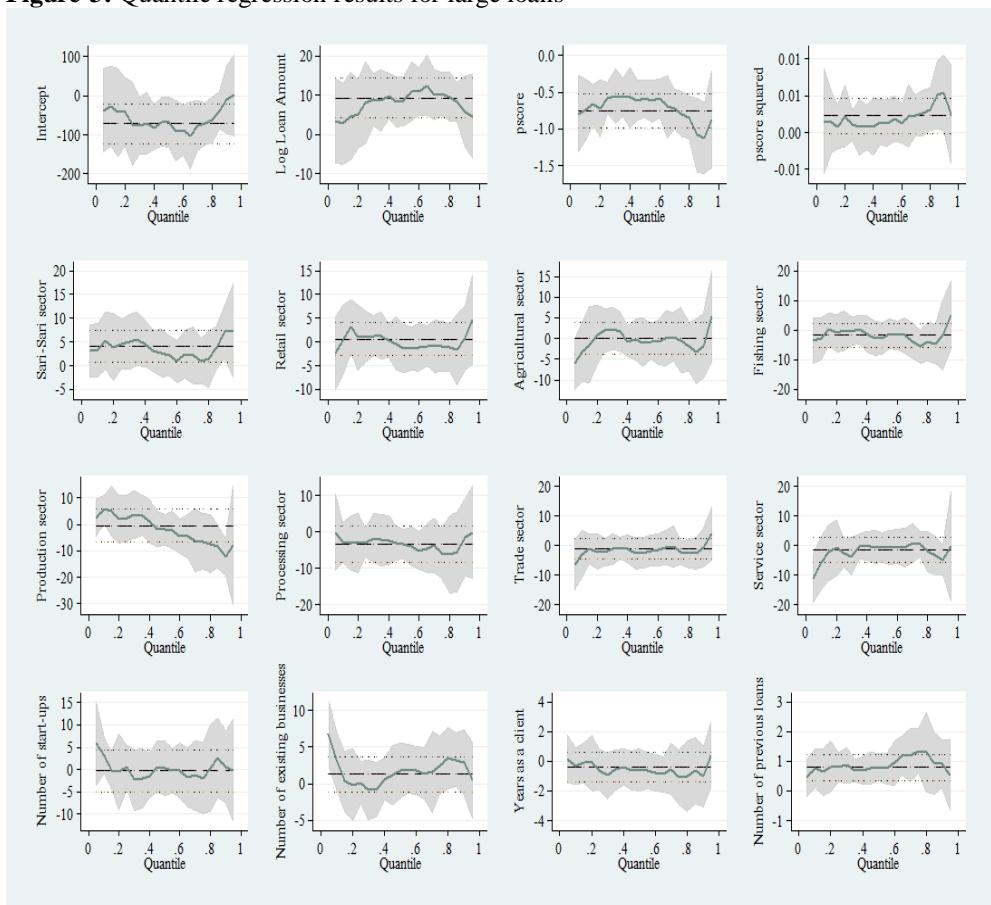
**Figure-1:** Quantile regression results for all loans



**Figure-2:** Net effect of initial poverty (pscore) by percentile, for all loans



**Figure-3:** Quantile regression results for large loans



## Conclusions

The analysis in this paper was aimed at the empirical determinants of poverty movement within the micro-lending program of the NWTF. In particular, estimation was targeted to test observable characteristics of actual borrowers that the literature indicates might serve as pre-conditions for success.

Results show that clients do, on average, become wealthier as borrowing members of the NWTF. The average client gained 1.51 points on their poverty score card, a rise that seems large only in context. Considering that a 2-point rise is equivalent to the replacement of walls or roof made of light materials such as bamboo with strong materials such as concrete or iron, these are very real gains in the fight against poverty. In concrete terms, the NWTF program is effectively reducing poverty.

Further, larger loans are clearly associated with even larger improvements, a result true at all percentiles, but particularly powerful near the top percentiles. This suggests that more NWTF funding might be even more effective, without the need to find new clients. Instead, encouraging current clients to grow from smaller to larger loans appears to serve clients' interests.

Greater initial poverty increases the chances of improvement, with clients below the twenty-fifth percentile enjoying much larger improvements than their peers, other things held equal. (For example, clients with initial poverty scores of 25 or less gained an average of 12.77 points, while clients with poverty scores above 25 lost an average of 3.51 points. Given these two results, the obvious policy advice would be to consolidate efforts into fewer, larger loans and to re-engage efforts to identify methods of reaching the ultra-poor, who are the primary beneficiaries of the NWTF program.

The economic sector of client activity matters greatly, and the estimates suggest quite clearly that loans to pursue activity in the sari-sari, service and trade sectors will be more productive in generating progress against poverty than will equal loans to activity in the

agricultural, manufacturing/production or fishing sectors. Moreover, clients investing in existing businesses enjoy consistently and significantly better outcomes than clients who invest in startup businesses, an effect not reversed for serial entrepreneurs but even more pronounced for those who invest in multiple startup businesses.

Finally, improvements in poverty scores take patience. Each additional year as a client, or successive (and successful) loan, increases the client's average change in poverty score. This evidence should encourage NWTF to continue their current work, maintaining ties with current clients over time, to nurture these anti-poverty effects into full maturity.

In conclusion, micro-finance is working in the fight against poverty in the Philippines, and it is the hope of the authors that this analytical work will help it to work even better.

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