Staff Incentive Policies for Credit Officers: An analysis of their heterogeneous effects on productivity*

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Abstract

This paper examines how changes in monetary staff incentive contracts affect the productivity of credit officers within microfinance institutions. We analyze a panel data set comprised of various productivity indicators at the credit officer level from five microfinance institutions in Peru, each of which increased the power of their incentive scheme. In each institution, the variable portion of the salary which is tied to productivity indicators was increased. Although the increases in the power of the incentives improved productivity, the performance of a large proportion of employees was unaffected. Two major reasons for this lack of response among some employees are the existence of non-linearities in the contract design and differences across the geographic areas in which credit officers operate. The results do not find a negative substitution between the two primary dimensions of the incentive contract: quantity of portfolio and quality of portfolio, but there is evidence of a negative substitution effect away from poorer clients.

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1. Introduction

Significant resources have been employed over the past several decades by governments, international donor organizations, and private investors towards the strengthening and expansion of micro-finance institutions (MFIs). Microfinance institutions are institutions (both for-profit and non-profit) that specialize in loans and savings products for individuals who do not have access to the formal banking sector. Although there are no reliable estimates on how many MFIs exist, more than 1,500 MFIs serving over 30 million families responded to a recent survey by the Microcredit Summit Campaign.[1]

The key difference between a microfinance institution and a bank is that in a bank, loans are processed primarily in the branch office and are based upon formal financial records and legal guarantees. In microfinance institutions, the authorization process is based upon a field-based socio-economic analysis aimed at determining capacity and willingness to repay the loan, and/or guarantees from other individuals or groups of individuals in the community.

Within microfinance institutions, credit officers are responsible for the promotion, screening, monitoring, and enforcement of loans. They account for about half of an institution's input costs (in the form of salaries) and critically affect the overall performance of the institution. Direct monitoring is difficult as credit officers spend about 75% of their time outside of the office visiting clients or potential clients. Over the past three to five years, a large percentage of microfinance institutions have switched from a fixed salary compensation scheme to one that includes a pay-for-performance compensation component based upon various performance indicators. This shift has been accompanied by another trend towards a "commercialization" of the microfinance industry that is characterized by increased competition and a shift from donor assistance towards a greater focus on sustainability and profitability. Despite the perceived importance of staff incentive policies for the performance of MFIs, little is known about the effectiveness of such policies.

The goal of this paper is to determine the nature and magnitude of the effects of staff incentive policies on performance indicators of credit officers. In addition to estimating the average effect due to an increase in the power of an incentive scheme, we investigate whether there are differential effects across indicators (due to possible substitution between tasks), across credit officers (as determined by initial productivity levels), and contexts (rural vs. urban).

This study contributes to the relatively small but emerging empirical literature on the role of incentives within institutions. Empirical work on the importance and effectiveness of incentives for employees has been limited due to a scarcity of data: only a few studies in very specific workplaces have been conducted over the past decade. This study is significant because the richness of the data set collected permits an exceptional opportunity to empirically test some of the predictions of the multi-tasking agency literature. We are also able to examine the effects of non-linearities in the contract design as well as the heterogeneity of incentive effects across agents and the contexts in which they work. Previous work has hinted at a possible effect of

[1] Microcredit Summit Campaign Report, 2001.

differences across geographic areas[2], but there has yet to be a thorough analysis to gauge the potential importance of this phenomenon on the effectiveness of incentives. It is important to note that we utilize actual data on contractible productivity measures as well as the incentives paid; most previous studies on the effects of incentives have proxied the effects using payroll data.

The panel data collected for this study includes monthly productivity indicators at the credit officer level for 316 credit officers from five microfinance institutions in Peru. The data corresponds to several months before and after a significant increase in the incentive scheme. We utilize differences in implementation dates across institutions to control for possible seasonal or macro-level shocks that might affect productivity.

We estimate the average treatment effect of introducing the stronger incentive scheme and to what extent the treatment effects vary across individuals, branches, institutions, and tasks (maintaining quality of portfolio, increasing quantity of portfolio, and providing loans to poor clients) using a fixed effects estimation strategy to control for unobserved credit officer characteristics. On average, we find a significant increase in productivity as measured by value of outstanding portfolio. However, despite an average 30% increase in the intensity of the incentives, a large proportion of credit officers did not respond to the higher incentives. While this might seem puzzling within a standard principal agent theoretical framework, it is consistent with our expanded set of predictions that account for non-linear contracts and heterogeneous local market conditions. A closer examination of the effects across different performance indicators reveals no substitution effect between quantity and quality of portfolio. In two of the five institutions, the two non-profit institutions, we do find a significant shift towards higher average loan size. Although not conclusive, this might imply a shift away from poorer clients. While the effect of the increase in the incentive payments has a positive effect on productivity, the results also expose some critical limitations of the incentive schemes.

The remainder paper is organized as follows. In Section 2, we discuss how the study relates to the existing empirical incentives literature, describe the design and structure of the incentive contracts, and summarize findings of qualitative research on the effects of the incentive schemes. In Section 3, we identify the principal predictions on the effects of increasing the power of the incentives that are derived from the existing agency literature as well as from the information gathered through field interviews with credit officers and managers. The data set and some summary statistics are discussed in Section 4. Section 5 outlines the empirical strategy and empirical results on the average treatment effects across the performance indicators. The results of the investigation into differential effects across credit officers and contexts are presented in Section 6. In Section 7, we discuss the key conclusions.

[2] For example, in Asche (1990), there is a reference to the fact that the ability to meet quotas for navy recruiting varies considerably across geographic areas of the U.S. However, the study could not further investigate this issue since the data set was restricted to the Chicago area.

2. Background and Context

2.A. Staff incentives and agency theory

A number of agency (or "moral hazard") models have been developed to analyze the choice of contracts and their effects when monitoring of employee effort is imperfect and/or costly. There have been several important extensions to the standard principal agent model, particularly in the past five to ten years. The principal agent model that originally focused only on the efficiency vs. insurance trade-off (Grossman and Hart, 1983 and Stiglitz, 1974) has been expanded to include: multiple agents, multiple principals, multiple periods, multiple tasks, intrinsic motivation, and several other special cases. Each extension brings us closer to modeling the complexities of reality and the diversity of economic environments. Unfortunately, the empirical studies to test such improved theories have been remarkably limited.[3]

Much of the interest within the agency literature has focused on the question of whether incentives matter: to what extent do agents respond to incentives? Because of the scarcity of data, only a few studies have been able to directly estimate the productivity effects of staff incentive contracts. In a study of employees of a windshield installation company (Lazear, 1996) and a study on horse jockeys (Fernie and Metcalf, 1996), significant and sizeable increases in productivity were found following the adoption of incentive or "piece rate" contracts. Similarly, a study found that the introduction of an incentive scheme increased productivity of check clearing clerks by 16% (Copeland and Monnet, 2002). Using a more structural approach, Paarsch and Shearer (1996) find increases in productivity of between 6% and 30% among tree planters working under an incentive versus a fixed wage scheme. Shearer (1999) documents 20% higher productivity among tree planters who were randomly assigned to piece rate versus fixed wages.

Within the incentives literature, there is also an interest in exploring the implications of contracts in which agents are expected to perform more than one task. Although there have been very few empirical studies of Holmstrom and Milgrom's "multi-tasking theory" (Holmstrom and Milgrom, 1991), the initial results have been interesting. Using probit models for the type of contract between oil firms and service station, Slade (1996) finds evidence that the contracts between oil firms and level of incentives varies depending upon whether or not the service station performs complementary tasks. Preyra and Pink (2001) find that CEOs of non-profit hospitals (who have multi-dimensional objectives) receive lower powered incentives than those directing for-profit hospitals. Cockburn, et. al. (2000) investigate incentive schemes for researchers in pharmaceutical laboratories. They find a positive correlation between the use of incentives for different tasks (basic vs. applied research): an increase in incentives for one task is matched by increasing incentives for the other task, presumably in order to avoid unintended distortions in effort. These studies have analyzed whether the design and/or utilization of observed contracts coincides with theoretical predictions. Our study will be the first to directly measure potentially differential effects of the incentives across tasks.

[3] See Gibbons (1998), Prendergast (1997), and Chiappori and Salanie (2000) for fairly comprehensive reviews of recent empirical contract literature.

The implication of non-linearities in the design of incentive contracts has been identified as a critical factor affecting agent behavior. An important study by Asche (1990) demonstrates the importance of non-linearities (i.e. minimum cut-offs) in the incentive contract. Navy recruiters are more productive in the months before the incentive pay-off if they are closer to their minimum target than if they are further away. Copeland and Monnet (2002) show that a minimum productivity standard (discontinuity in the compensation function) can reduce the effectiveness of an incentive scheme.

The study of the effects of incentives has almost exclusively focused on the "average effects" of incentives across all agents. We know little about how the effectiveness of an incentive contract can vary across agent characteristics and/or the context in which the agent operates. Asche (1990) notes that there are important differences in the ability of navy recruiters to meet recruitment quotas across different geographic areas of the U.S. However, since the data utilized in that study was restricted to the Chicago area, the potential for heterogeneity of agent response across areas could not be examined.

2.B. Characteristics of staff incentive policies within microfinance institutions

Although the incentive schemes utilized by microfinance institutions vary across institutions, we can identify some similarities in structure and design of these schemes. Based upon research (qualitative and quantitative) with 14 microfinance institutions in Peru, Nicaragua, and Mexico, the common characteristics of these schemes are:

- *Unit of analysis*- The incentives are calculated at the individual credit officer level rather than group or branch level (only one of the 14 institutions used branch rather than individual-level incentives)
- *Frequency of payments*- The incentives are typically paid out at the end of the month based upon the performance indicators at the close of the month (three of the institutions had switched from quarterly schemes to monthly schemes, one pays bi-weekly, all others are monthly)
- *Incentive formula*- All schemes are based upon at least two performance indicators (average of three to four) and are piece-wise linear: if certain conditions are met, the payment scheme is a linear function in each task.[4] A minimum threshold must be met before incentives are paid out. Also, if the minimum threshold is not met for one of the indicators, the agent is often not allowed to receive any incentives for the month.
- *Indicators*- The primary indicators used are: value of outstanding portfolio, delinquency rate, and number of current clients. Additional indicators utilized by some institutions include: growth in value of outstanding portfolio, new clients, number of new clients, net growth of clients, and value of disbursements.
- *"Power" of incentives*- The average ratio of (incentives paid)/(fixed salary), a rough measure of the "power" or intensity of the incentives was typically between 10% and 20% across the 14 institutions. This ratio was much higher, typically between 20%-40% among credit officers that received any incentives.
- The percentage of credit officers that received any incentives in a given month (i.e. met the minimum benchmarks) varied between 18% and 81% across institutions.

[4] In some institutions, the "linear" section of the incentive scheme is actually a series of payoffs corresponding to much smaller cut-off ranges. As long as these cut-off ranges are perceived by the agent to be relatively small, then these schemes can be considered comparable.

2.C. Design and structure of staff incentive policies within microfinance institutions

Although each incentive scheme is unique, there are remarkable similarities in the schemes across microfinance institutions whether large or small, private/regulated (for-profit) or non-profit. The following description of an incentive scheme is utilized by one of the institutions in this study and can serve as an example of a typical scheme.

Description of an incentive scheme
The incentives are calculated and paid on a monthly basis at the individual credit officer level. The three indicators used for the calculation of the incentives are: value of outstanding portfolio, number of current clients, delinquency rate (>30 days). The incentives are only paid if the credit officer achieves the minimum requirements for number of clients (>200) and delinquency rate (<8%). The incentives for each variable are a simple linear function and then are summed to determine the overall incentives.
Definitions: P = outstanding portfolio (in US$) N = number of clients D = delinquency rate (>30 days) Benchmarks for each indicator: P = $300,000 N = 400 D = 8% Formula: {.3*(P/300,000)+ .2*(N/400) + .5*(.08 – D)*100}*$300 If D > 8% or N<200, no incentives are paid for any of the indicators.

This contract form seems rational from the MFI's perspective. The MFI only earns a profit if the credit officer has sufficient quantity (value of portfolio) and quality (low delinquency rate) of portfolio. Both outputs must be met as profit is a multiplicative function of these two outputs. A credit officer could have a 100% repayment rate, but this is only important to the MFI if the credit officer has a significant volume of loans. Similarly, a credit officer could have a very large loan portfolio, but this is only of value to the MFI if the repayment rate is very high.

Since profit is a direct product of size of portfolio and repayment (i.e. low delinquency), then we might be surprised by the inclusion of the indicator for number of clients. MFI managers often utilize "number of clients" as an indicator as a risk mitigation strategy.[5] Another, even more important reason is to minimize the effects of differences in local market conditions faced by credit officers.[6]

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[5] MFIs prefer to have their portfolio distributed across several smaller loans rather than a limited number of very large loans to reduce their risk exposure.

[6] Credit officers operating in less wealthy areas would have to spend much more effort and time per dollar lent than credit officers operating in better areas. However, the effort and time spent to generate a new client is similar regardless of the type of client. This issue is discussed in greater detail in the next section.

2.D. Perceived effects of staff incentives: evidence from qualitative research

The qualitative component of this study involved in-depth interviews with 250 managers, branch managers, and credit officers in fourteen MFIs in Nicaragua, Mexico, and Peru.[7] The interviews included both likert scale questions as well as more open-ended questions to gather information on perceptions of the incentive schemes and their effectiveness.

The managers of the MFIs were particularly concerned about a possible negative effect of the incentive scheme on delinquency rate. They worried that some credit officers might increase the quantity of their portfolio to earn more incentives in the short-term, with a negative effect on the quality of the portfolio over the medium term. The managers were also unsure about the extent to which the credit officers were responding to the incentives. When first implementing the incentive scheme, they had envisioned a scenario whereby all credit officers would eagerly work towards increasing their incentives and thus the MFI's productivity. However, they were not as happy with the response of the credit officers to the incentives as they had expected.

Qualitative results from the interviews with credit officers suggest that incentives can have powerful effects over productivity, but only for about 40% of the credit officers. When asked if they had changed their behavior following the implementation or a recent increase in the power of the incentive scheme, almost 60% of the credit officers said they had not. Most of these did not meet the minimum cut-off levels (particularly for the delinquency rate) to qualify for the incentive compensation (both before and after the increase in the power of the incentives). Many felt that the cut-off levels and benchmarks for performance indicators were unfair given the difficulties of their operating area. Generally, there exists a uniform incentive scheme (with established parameters and payoffs) for all credit officers within an institution despite the fact that the institution might operate in very heterogeneous contexts. Credit officers are assigned certain geographic areas in which they are to operate. Credit officers that operate in especially poor areas or areas that are more distant from the branch office (clients are less willing to make deposits if they live very far from the branch office) feel like they are being treated unfairly by the incentive scheme (they have to work much harder to attain the same performance parameters). Rather than being motivated by the incentive scheme, some of credit officers report becoming ***less*** motivated.

For many of the credit officers (about 40%), however, the increased salary potential of the incentives was a significant force that resulted in an increase in motivation and productivity: "Yes. Of course I did [work harder]- I realized how much more I could earn." Another credit officer at a non-profit institution said, "Before the incentive scheme, none of us wanted to open new [village banks]. We would fight among ourselves to decide who would have to open the new group. Now, it is the opposite, we are all looking for ways to help form new groups. We all need the extra money."

For the credit officers who reported higher productivity, they were pressed to explain exactly how they had changed their behavior. Some of the more common responses were:

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[7] A companion paper presents the complete findings and implications from the qualitative research phase of this project: "Improving the effectiveness of staff incentive policies for microfinance institutions," [paper in progress], 2004.

- Work later hours. Credit officers can begin to work more on paperwork in the evenings in order to save time during the day to visit clients.
- Spend more time in the field. Many feel the best way to make a good credit evaluation, find new customers, and to control delinquency, is to spend as much time in the field as possible. Before, they would spend more time around the office "chatting" with their co-workers.
- Organize work more efficiently. This can be achieved through more efficient means of processing paper work or through concentrating efforts in a specific geographic area. Much of the time of a credit officer is spent traveling from one client to another. By concentrating in certain areas, the credit officer can save travel time while increasing monitoring (can visit each client more often through drop-by visits) and promotion (most credit officers prefer to attract new clients through referrals of current clients).
- Concentrate on wealthier clients and larger loans. Some credit officers said they could increase their outstanding loan portfolio much quicker through say ten new $2,000 loans than through forty $500 loans. The evaluation process (fixed costs of processing a new client) is often similar in terms of time and effort. However, there are significant checks on this strategy. First, the effort to find and attract wealthier clients might actually be more difficult if there is greater competition from other institutions for this same market segment. Second, credit officers feel that their portfolio is more susceptible to risk when it is concentrated in a smaller number of larger loans. Often, they feel it is easier to control delinquency among the forty $500 loans than among the ten $2,000 loans.
- Allocate work among tasks more efficiently. The principal trade-off in a credit officer's allocation of effort is between controlling delinquency and increasing loan portfolio. If they are not receiving incentives because of insufficiently large loan portfolio (while the delinquency rate is in control), then they will allocate more time towards generating new clients. If their delinquency rate is too high they would choose to actively pursue the easiest delinquent cases first and the more difficult ones later.

3. From Theory and Fieldwork Towards Predictions

Our selective review of previous work within the agency literature suggests specific types of effects we might expect resulting from an increase in the power of an incentive scheme ("treatment"). Findings from the field research with managers and credit officers also contribute towards formalizing our predictions of these effects. Here are three predictions that we will empirically investigate:

Prediction 1: The treatment will result in an ***average increase in productivity*** across indicators.

- Standard agency theory and previous empirical studies of the effect of piece rate contracts on employee productivity suggest we will see an increase in productivity due to the increase in the piece rate.
- Qualitative research also suggests that credit officers respond to the treatment by increasing productivity.

Prediction 2: The treatment might result in ***negative impact on some indicators*** due to negative substitution between tasks.

- The multi-tasking literature suggests we might see a diversion of effort away from tasks if they are not included in the contract or if the marginal cost of effort in one task is greater than for another task.
- Although microfinance managers were concerned about a possible diversion of effort away from recovering loans, the non-linear contract (maximum permitted delinquency rate) seems to be (based upon qualitative interviews) an effective deterrent to increasing the delinquency rate.
- There is also a concern that the treatment might cause a shift in effort away from poorer clients towards wealthier clients. As discussed above, credit officers might be motivated to do so because they can spend much less time per dollar lent when lending to wealthier clients than to poorer clients.

Prediction 3: The treatment effect will vary across credit officers, depending upon their ***initial productivity level*** and ***local market conditions***.

- This result stems primarily from the non-linear form of the incentive contract. If credit officers have an initial productivity level that is far below the minimum cut-off, than an increase in the piece-rate will not result in an increase in productivity (i.e. they do not receive any incentives before or after treatment). If credit officers have an initial productivity level that is near or above the minimum cut-off standard, then they would likely respond to the treatment by increasing effort.
- One of the underlying reasons for having a low initial level of productivity could be the fact that the credit officer is assigned to work in a relatively difficult area (i.e. poor local market conditions or longer travel distances between clients). The interviews identified this as one of the major limitations on the effectiveness of the incentive scheme.
- In our case, the "minimum cut-off" for delinquency rate is frequently binding while the minimum cut-off for outstanding loans or number of clients is usually only temporarily binding for the first few months of tenure for an employee.

4. Data

4.A. Description of the data set

The panel data I have collected includes monthly productivity indicators at the credit officer level for five microfinance institutions in Peru. The data corresponds to several months before and after a significant increase in the power of the incentive scheme. Data from an additional two institutions will not be used because of other confounding institutional changes during the period of study. None of the five remaining institutions have experienced any significant internal or external changes during the period of study. In particular, there were no changes in: products (types and terms of loans), management information systems, or human resource strategies (i.e. monitoring and/or firing of employees, non-monetary incentive schemes).

Considerable effort was made to identify all MFIs in Peru that met the following three criteria for participation in the study: a) had introduced a new incentive scheme or significantly increased the power of an existing incentive scheme over the past couple of years, b) had monthly productivity data available at the credit officer level both before and after the significant change in the incentive scheme, and c) did not experience any other significant institutional changes around the period when the change in the incentive scheme occurred. No other institutions were identified (through direct e-mails and/or through key informants such as consultants, other MFI managers, and organizations of MFIs)

Summary information on the exact dates of the corresponding data and sizes of the institutions is presented in Table 1. Basically, the monthly institutional data has been coded into a single timeframe (whereby month 1 for MFI 1 is the same as month 1 for all the MFIs, etc.) beginning with June 2000 and ending in July 2003. The months for which I have data are labeled according to this timeframe. This placement on a single timeframe will enable us to better correct for seasonal or macro-level shocks that affect all institutions.

Table 1: Composition of Data Set

	Governance Structure	*# of Branches*	*# of credit officers*[8]	*Months of Data Availability: 1 = 6/00 31= 12/02*	*Month of Major Change in Scheme*
MFI 1	Non-regulated	11	127	1 – 28	20
MFI 2	Non-regulated	2	14	8 – 31	19
MFI 3	Regulated	12	84	15 – 31	23
MFI 4	Regulated	6	54	8 – 31	23
MFI 5	Regulated	2	37	15 – 31	25
Totals for 5 MFIs		33	316		

Data at the credit officer level was unavailable prior to the implementation of the institutions' first monetary incentive scheme. However, the increase in the power of the scheme is very significant in all cases (in some cases, the original scheme was so weak it could almost be considered non-existent). In three of the MFIs, the managers replaced a quarterly scheme with a monthly scheme (i.e. tripling the power of the incentives). The other two institutions had a monthly scheme in place and significantly increased the value of the bonuses across all indicators.

4.B. Context of the MFIs and reasons for increasing power of the incentives.

Two of the five MFIs are non-regulated NGOs and the other three MFIs are regulated privately owned enterprises. The regulated MFIs are forced to abide by stricter regulations and tend to be more commercially oriented. Although all five MFIs have professed a "social mission," only MFI 1 is subsidized (by international donors) to explicitly serve poor clients. MFI 2 is an NGO that no longer receives subsidies and must break even. MFIs 3, 4, and 5 are all aiming to

[8] The number of credit officers refers to the total number of credit officers over the entire study period for each MFI. The number of credit officers for each MFI at a given time is considerably less.

maximize profit. Only MFI1 utilizes the community banking lending technology while the other four MFIs lend to individuals (with 1-2 loan guarantors).[9] MFIs 2 and 5 only operate in large cities while MFIs 1,3, and 5 operate in large cities but have also have a presence in smaller towns and rural communities.

The qualitative interviews with MFI managers help to provide more information about the decision to adopt a staff incentive scheme and why they later significantly increased the power of the scheme. The initial decision to adopt a monetary staff incentive scheme is similar to a standard technology adoption decision. Before 5 years ago, only about 5% of the MFIs in Peru had a monetary staff incentive policy. Beginning about 4-5 years, MFIs in Peru began to hear from consultants and donors that MFIs in other countries were having successful experiences with staff incentive schemes. As some of the larger and more influential MFIs in Peru began to implement staff incentive schemes, the other MFIs heard that they were working and decided to implement their own schemes.

However, when they first implemented the schemes, the incentives schemes were very weak (i.e. low ratio of variable salary to fixed salary), for two major reasons. First, the managers were worried about possible negative impacts of the incentives on quality of portfolio and in making mistakes in calibrations whereby the costs of the incentives could be much higher than they anticipated. Secondly, due to wage rigidity, the managers were unable to reduce the fixed salary of the workers and increase the incentive payments: the incentive schemes had to be additional compensation.

After a trial period of 1-2 years, many of the MFI managers realized that the incentive schemes had not caused serious negative effects on the quality of portfolio and did not cost too much. Furthermore, they heard from the workers and branch managers that the power of the incentive schemes was quite weak and that greater incentive payments would probably increase productivity. It is important to point out that the inflation during the entire study period was close to 0%- therefore the increase was not meant to adjust for inflation (all values in the dataset have been corrected for inflation on a monthly basis).

4.C. Summary Statistics

Summary statistics of credit officer performance across institutions, before and after the increase in the power of the incentive scheme (the "treatment"), are presented in Table 2 (on the following page). These statistics (and all analysis in this paper) reflect averages across credit officers and are not weighted by portfolio size. Since our focus is on the effects of incentives on credit officers, this data format is suitable for our purposes. However, it is important to point out that these statistics are not directly comparable to a weighted average of the institution.[10]

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[9] Under community banking technology, the credit officer helps to form groups of 15-25 individuals who agree to mutually guarantee the loans of all community bank members. The loan sizes start off much smaller and increase gradually upon successful repayment cycles.

[10] For example, if an MFI had 2 observations for loan delinquency rate: .05 and .15, the average delinquency rate across credit officers would .10. However, in actuality, if the first credit officer had a larger portfolio, then the average institutional delinquency rate would be less than .10.

We see that there are very large differences across MFIs, particularly for outstanding portfolio, number of clients, and average loan size. Performance indicators seem to substantially improve after the increase in incentives (treatment). However, it is important to point out that much of the increase in performance indicators could also be attributed to an increase in average tenure. Staff turnover was quite high both before and after the increase in incentives, with an average drop-out or attrition rate of about 1.05% per month. The increase in compensation paid in the form of incentives was relatively important for all institutions except for MFI4, where the average increase was less than 50 Soles. To give an idea of the relative "power" of the incentives, the monthly base salary ranged between S/900 and S/1500 across institutions[11].

[11] Approximate exchange rate is 3.5 Soles = 1 US$.

Table 2: Summary Statistics Across Institutions, Before and After Treatment Effect (T)
Standard deviations are presented in parentheses

	MFI 1		MFI 2		MFI 3		MFI 4		MFI 5		Total
	Before T	After T	Before T	After T	Before T	After T	Before T	After T	Before T	After T	
Outstanding portfolio (in Real Soles, approx. 3.5 Soles per US$))	88,672 (62,062)	136,250 (66182)	262,230 (43,847)	369,326 (104,568)	783,256 (433,750)	894,436 (427,442)	403,203 (183,760)	495,742 (212,866)	312,278 (127,369)	350,155 (104,459)	377,706 (374048.6)
Number of clients	145 (83.2))	211 (86.30)	171 (20.8)	201 (33.4)	279 (150.5)	311.1 (151)	152 (65.6)	176 (65.7)	129 (51.8)	141 (39.9)	197 (115.3)
*Delinquency rate**	5.2% (.099)	6.3% (.116)	9.4% (.052)	6.9% (.060)	13.8% (.091)	12.3% (.092)	7.2% (.041)	7.0% (.042)	9.5% (.05093)	8.8% (.04681)	**
Average Loan Size (Real Soles, approx. 3.5 Soles per US$)	570 (118.5)	628 (123.97)	1,535 (188.9)	1,821 (404.5)	2,762 (602.5)	2,876 (625.4)	2,622 (393.97)	2,764 (410.44)	2,428 (195.12)	2,480 (206.46)	1,753 (1091.4)
Average tenure (in months)	8.4 (5.85)	15.1 (7.19)	14.9 (5.87)	24.3 (9.70)	16.7 (7.52)	22.7 (10.14)	13.9 (7.78)	21.3 (10.89)	15.5 (8.77)	20.9 (10.39)	15.4 (9.53)
Average rate of staff attrition (per month)	1.29% (.113)	1.57% (.125)	1.10% (.1045)	0.55% (.0741)	0.35% (.059)	1.46% (.1198)	0.76% (.0870)	1.03% (.1010)	1.00% (.0993)	0.39% (.0621)	1.05% (.1018)
Avg monthly change in Outstanding Portfolio (Real Soles)	7,520 (11,261)	7,152 (15,574)	4,032 (12,418))	12,428 (15,596)	10,449 (50,020)	25,006 (44,833)	10,743 (31,945)	16,061 (27,639)	4,843 (12,757)	7,394 (9,948)	11,042 (28822.7)
Avg monthly change in Number of Clients	11.2 (14.14)	10.3 (17.5)	2.0 (3.60)	3.6 (4.86)	3.8 (17.19)	7.3 (16.41)	3.4 (7.65)	4.5 (8.32)	1.5 (4.94)	2.6 (3.90)	7.1 (14.07)
Avg. monthly change in Delinquency Rate	.0082 (.041)	.00003 (.028)	-.0005 (.0086)	-.0017 (.0043)	.0015 (.0161)	-.0019 (.0097)	.0016 (.0060)	-.0008 (.0041)	.00029 (.0024)	-.00082 (.0021)	.0019 (.0247)
Avg. percentage of credit officers receiving incentives	16.8% (.3738)	67.1% (.4701)	2.2% (.1482)	43.8% (.4979)	49.6% (.5005)	59.0% (.4922)	26.7% (.4430)	31.5% (.4651)	45.8% (.5012)	55.2% (.4985)	40.4% (.4907)
Average monthly incentive compensation (Real Soles)	35.4 (137.9)	172.2 (154.4)	2.3 (28.78)	243.7 (263.1)	177.3 (196.4)	473.3 (435.9)	34.81 (71.4)	82.64 (137.4)	77.5 (279.4)	322.21 (306.8)	197.9 (275.1)
Observations:											
Number of observations	1,216	827	110	137	532	612	519	368	277	201	4,799
Number of credit officers	117	104	12	12	72	79	45	47	35	30	316
Avg. # of obs. per credit officer	10.4	7.95	9.17	11.42	7.39	7.75	11.53	7.83	7.91	6.7	15.2

** The delinquency rate is not directly comparable across institutions due to different definitions.*

Note, the values presented are Real Soles adjusted on a monthly basis using month 19 as the base value. The exchange rate was approximately 3.5 Soles per US$.

All of the indicators are comparable across institutions except for the delinquency rate. For most institutions, the statistic I am presenting is the value of portfolio that is more than 30 days past due divided by the entire outstanding portfolio. For one institution the number of days past due is different. The data for another institution corresponds to portfolio at risk, which is essentially a weighted measure of the delinquency rate (with substantially higher weights to amounts that are more days past due)

The indicators of average monthly changes (for outstanding portfolio, number of clients, and delinquency rate) are generated for each month by subtracting last month's data from the indicator for this month (i.e. change in number of clients for month 2= number of clients in month 2 minus number of clients in month 1). By construct, a new credit officer will not have this indicator until his/her second month. I did not include any new portfolio or clients that were *transferred* to a credit officer during a month (this affected 18 cases). [13]

4.D. Staff Turnover

There is a degree of staff turnover over the 31 month study period with an average rate of staff attrition of 1.05%. When a credit officer leaves an institution (either voluntarily or fired), in about 90% of the cases, the credit officer's portfolio is transferred to a new credit officer. In about 10% of the cases, the old portfolio is divided whereby an experienced credit officer receives a portion and/or a new credit officer receives a portion. I have information that permits me to track where the portfolio of a departing credit officer goes.

In order to better understand this phenomenon of staff turnover, we can take a closer look at the reasons for staff leaving an institution. For two of the institutions, I have information on why a total of 49 employees left the institution over the study period as recorded by the director human resources.[14] The principal reasons were as follows:

Table 3: Reasons for Staff Attrition

Principal reason for leaving	1st MFI	2nd MFI	Total
Fired for theft, fraud, or gross negligence	6		6
Fired for poor performance or behavior	13	5	18
Left voluntarily for personal reasons	4	3	7
Left voluntarily for a job in another institution	11	2	13
Transferred or promoted within institution	5		5
Total	**39**	**10**	**49**

A comparison of the pattern of these reasons before and after treatment does not appear to reveal any systematic differences. In fact, the reasons for staff turnover are somewhat more random than we might originally expect. Even among the credit officers that were fired for "poor performance", the reasons were as varied as: showing up to work drunk, being rude to clients, sloppy handling of paperwork, and performance (measured by quantitative parameters) below

[13] I would like to isolate this flow indicator from excessive noise and to try to ensure that it would better reflect a credit officer's effort (i.e. it is much harder to generate 100 clients than to have them transferred to you from a leaving credit officer).

[14] This represents 85% of the total number of employees that left in those institutions and 57% of the total number of employees that left all five institutions.

expectations. Employees leaving for personal reasons included credit officers who: had to move because of spouse's employment, wished to spend more time with children, left for health reasons, and those who quit because they did not like the nature of the work or the work schedule. There is also considerable competition for credit officers among microfinance institutions; although incentives are part of the agent's decision problem, it seems that differences in the base salary are even more important (based upon the qualitative interviews). The base salary in the 1st MFI listed above was significantly lower than that of the other MFIs and several employees did in fact leave to work for another MFI (both before and after the increase in incentives). In one of the MFIs I studied, not a single employee had left to work for another institution, because they were already receiving the highest base salary in the market.

We are particularly interested in the nature of staff turnover because we might expect the increase in incentives to affect (either increase or decrease) staff turnover. In particular, we might expect staff turnover to decline following an increase in the incentives as the better workers are more willing to remain with the institution. On the other hand, we might expect either a constant or a higher turnover rate among the lower ability workers as a result of the increase in incentives. Overall, the monthly attrition rate increased slightly from an average 0.90% before the treatment effect to 1.31% after the increase in incentives (statistically significant at the 10% level).

In ***Annex 1***, there is a detailed tracking of the turnover rate by institution and level of employee productivity.[15] Each month, by institution, the workers were classified by quartile according to the value of their outstanding portfolio.[16] The average monthly turnover rate was calculated among credit officers of each quartile of each institution both before and after the increase in the incentive scheme. The aim is to see if there exist patterns whereby either the best or worst employees are leaving an institution.

The results show that there are some slight tendencies (not quite statistically significant) in MFI1 and MFI3 towards an increase in staff attrition among workers in the lowest quartile following the treatment. In MFI5, there is a hint (not statistically significant) of a decrease in staff attrition among the highest quartile employees.

Overall, this approach does not provide strong evidence of a consistent and powerful selection effect at least on the attrition of employees. This might be due in part to our relatively small sample size. It could also be due to a lack of a clear pathway of influence given the fact that there are several very diverse causes for staff attrition. The factors guiding the laying off of employees would most likely remain unchanged before and after the treatment effect. Similarly, policies for transfers and promotions and many of the personal reasons for staff attrition would not be affected by the incentive scheme.

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[15] Following the same approach used by Lazear (2000).

[16] A parallel exercise was carried out for the delinquency rate parameter; however, the results were almost universally insignificant across all quartiles.

5. Estimating the Average Treatment Effect

Our empirical strategy entails credit officer fixed effects regressions on the main performance indicators of the credit officers. The new incentive scheme is implemented at a certain point in time throughout each institution. The aim is to measure whether the implementation of the incentive scheme resulted in an effect on performance levels following this event after controlling for individual fixed effects, seasonality, and tenure in the institution. The discontinuity in time is the assignment mechanism and the identifying assumption is that no other shocks (internal or external) occurred around the time of the implementation of the incentive scheme (these assumptions are addressed below).

As discussed above, the treatment might affect productivity through a selection effect (higher skilled and motivated agents attracted to the institution) and an incentive effect (same agents exert more effort). It is important to point out that the estimation strategy utilized estimates the combined incentive and selection effect. Due to the relatively small sample size of new employees following the treatment, it is difficult to separate out any effect on the quality of new employees.

5.1 Assumptions and limitation of empirical approach

A potential limitation of the data set is the fact that the changes in the incentive schemes occur simultaneously throughout each institution. When we estimate all institutions jointly, we can use the differences in implementation dates across institutions to identify and control for macro-economic and/or seasonal shocks that might coincide with the implementation of an incentive scheme.

There are in effect **three specific assumptions** underlying the general empirical approach to estimate the **average effect** of the new incentive scheme:

1. We implicitly assume that there are no other **simultaneous unexplained shocks** at the level of the institution (other than the seasonal and macro-economic shocks that affect all institutions) that could affect performance indicators at the credit officer level. The most likely form of an institution-specific shock could be the introduction of other new policies by the MFI. This potential problem is being addressed by our decision to only include stable MFIs that have not implemented any other major initiatives or policies over the study period. The in-depth interviews with managers and credit officers confirmed that within these five MFIs, there were no significant changes in: credit products, management policies of delinquent loans, management information system, or human resource strategy during the time frame of the study. Two additional institutions were excluded from the study because of simultaneous changes of either an administrative (reorganization to include additional supervisors) or programmatic (changes in product rules) nature.
2. The second major assumption is that there is no **endogeneity problem** whereby the factors affecting the decision to implement/increase an incentive scheme also affect the efficiency/productivity of workers. For example, if the introduction/increase of staff incentive policies were implemented in response to a crisis or only in periods of high profitability, then it would be impossible to separate out the treatment effects. On the one hand, evidence from the field (in-depth interviews with managers of 25 MFIs) suggests that there is no strong evidence of either problem (implementing due to crisis or in periods of

high profitability). However, it is true that institutions decide to implement/change incentives if they feel that it will be cost-effective. Managers base their decision in large part on what they hear from consultants, donors, other institutions, and especially their own workers and branch managers.

We will test this assumption by looking for any significant positive or negative trends in the two-three months immediately prior to implementation of the new incentive scheme in each institution (after controlling for seasonality).

There is an inherent **self-selection** bias for choosing treatment (adoption of the new incentive scheme) whereby the only institutions that choose to adopt incentives are the ones that expect to benefit the most from it. However, this should not affect our analysis, since we are interested in assessing the effects of incentive schemes among institutions that have chosen to implement or change them.

3. The third assumption is that a significant portion of the **effect of the incentive policy can be accounted for** within the study time frame. This assumption can be explored through analysis of the data. It is probably reasonable to assume that the majority of the effects of the incentives could be accounted for within about 6-8 months following implementation of the incentive scheme. The average loan period is 4-5 months and the maximum loan period is 6 months. Loans are generally repaid in equal monthly (sometimes bi-monthly) installments, so a new delinquent client would show up in our dataset within one month.

5.2 Specification for estimating average treatment effect

The basic fixed effects regression equation is:

(1) $$y_{ijt} = \alpha_{ij} + (\delta_0 + \delta_1 X_{ij})T_{jt} + \beta_1 X_{ijt} + \beta_2 X_{ijt}^2 + \gamma_1 M_t + \varepsilon_{ijt}$$

y_{ijt} is the output of individual i of firm j in time t: it will either be log of outstanding portfolio, log of number of clients, delinquency rate, or log of average loan size

α_{ij} is a fixed effect for each individual of firm j meant to capture all time invariant observed and unobserved individual characteristics that affect productivity

X_{ij} is a vector of 4 firm dummy variables

X_{ijt} represents each individual's months of tenure in the institution (which varies over time)

T_{jt} is the treatment dummy coded as 0 for all months prior to treatment and 1 for all months following treatment at the level of institution

M_t is the vector of 11 monthly dummy variables to capture seasonal effects that could affect productivity

ε_{ijt} is the error term which captures unobservable effects on productivity at the individual level within each time period

Since the major productivity indicators are "stock" variables, there is a real concern about possible autocorrelation of the error terms. For example, a shock that affects the delinquency rate (or either of the other indicators) in time t would also likely affect the delinquency rate in time t+1. We will thus incorporate an assumption of autocorrelation of the first degree:

(2) $$y_{ijt} = \alpha_{ij} + (\delta_0 + \delta_1 X_{ij})T_{jt} + \beta_1 X_{ijt} + \beta_2 X_{ijt}^2 + \gamma M_t + \mu_{ijt}$$
$$\text{where } \mu_{ijt} = \rho\mu_{ijt-1} + \varepsilon_{ijt}$$

The hypothesis that ρ = 0 can be tested using a procedure that is similar to the Durbin Watson test, but specifically developed for panel data by Bhargava, Franzini, and Narendranathan.[17] If ρ is significantly different from zero, we will correct for the autocorrelation using the Cochrane-Orcutt estimator. Two main assumptions in using this estimator are that the correlation coefficient ρ is constant over the study period and across groups of individuals.

5.3 Estimation results of average treatment effect

Table 4: Fixed effects Regressions of Average Treatment Effect
(t-statistics are in parentheses)

	Nat. log of outstanding portfolio		**Nat. log of number of clients**		**Nat. log of average loan size**		**Delinquency rate**	
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**
Tenure (in months)	-.0536 (-6.23)	-.0563 (-6.54)	-.0698 (-9.13)	-.0705 (-9.20)	.0152 (8.84)	.0136 (7.76)	.0034 (3.08)	.0038 (3.33)
Tenure squared	.0011 (6.13)	.0011 (6.45)	.0012 (8.11)	.0012 (8.20)	-.0002 (-4.83)	-.0002 (-4.02)	-.0001 (-3.11)	-.0001 (-3.34)
Monthly dummy variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Treatment dummy	.042 (4.11)	.0287 (1.12)	.0305 (3.74)	.0244 (1.18)	.0084 (1.44)	-.0116 (-0.89)	-.0058 (-3.01)	-.0007 (-0.15)
Treatment * MFI 1		.0592 (1.92)		.0268 (1.08)		.0458 (2.94)		-.0090 (-1.59)
Treatment * MFI 2		.0548 (1.13)		.0190 (0.49)		.0858 (3.61)		-.0032 (-0.36)
Treatment * MFI 3		-.0256 (-.82)		-.0112 (-0.44)		.0000 (0.00)		-.0055 (-0.94)
Treatment * MFI 4		-.0302 (-0.88)		-.0115 (-0.42)		-.0053 (-0.31)		-.0009 (-0.15)
Coef. of autocorrelation	.86	.86	.87	.87	.67	.66	.81	.81
# of observations	4,398	4,398	4,398	4,398	4,398	4,398	4,398	4,401
# of credit officers	310	310	310	310	310	310	310	310
Modified Bhargava et al. statistic	.30	.31	.28	.29	.67	.70	.38	.38
Baltagi-Wu test stat.	.68	.68	.67	.68	.90	.92	.60	.60
Adj. R2 within	0.03	0.03	0.03	0.03	0.06	0.07	0.01	0.01
between	0.37	0.47	0.34	0.34	0.27	0.13	0.02	0.02
overall	0.38	0.45	0.43	0.43	0.20	0.11	0.03	0.03

In analyzing the simplest specification with an average treatment effect, we find that the treatment resulted in a 4% overall increase in outstanding portfolio, a 3% increase in number of clients, a .8% increase in average loan size and about a 0.6% decrease in the delinquency rate.

[17] Bhargava, A., L. Franzini, and W. Narendranathan. "Serial Correlation and the Fixed Effects Model." Review of Economic Studies, Volume XLIX, 1982, pages 533-549.

Most of the treatment effect appears to be coming from credit officers in MFI1 and MFI2, the two non-profit MFIs. Also, note that the average loan size increased by about 4% and 9% respectively within these two institutions. Although not significant, the point estimate for MFI1's treatment effect for delinquency is about .9%.

In summary, we have confirmed our prediction that there will be an increase in productivity for number of clients and value of outstanding portfolio. The multi-tasking hypothesis regarding an increase in delinquency rate was soundly rejected while the concern about a shift away from poor clients seems to be supported for the case of the two non-profit MFIs (the only two that would have an institutional interest in reaching poor clients).

Although not listed, the monthly dummy variables showed a slight peak in July and December for portfolio and number of clients (almost 2% increase) and for average loan size (almost 1% increase). There was less seasonal variation for the delinquency rate. We also see that there is considerable autocorrelation across specifications and we our test statistics confirm that we can reject the possibility that autocorrelation is equal to 0.

5.4 Timing of treatment effect

Thus far, we have been considering the treatment effect as corresponding to all months after the change in the incentive scheme. We can gain further insight into the nature of the effect by a closer examination as to exactly when do the effects of the treatment become evident. From a practitioner's perspective, it is important to see whether the effects on performance occur rapidly (1-2 months) or if credit officers respond slowly (5-6 months) to the change in incentives.

Also, an examination of the timing of the treatment effects can serve as a robustness check for possible concerns of endogeneity regarding the decision to increase the incentive scheme. Above, we discussed the possibility that other factors might affect the decision to increase the power of an incentive scheme which could also affect the efficiency/productivity of workers. We can test this assumption by looking for any significant positive or negative trends in the two-three months immediately prior to implementation of the new incentive scheme (after controlling for seasonality).

The following regression specification allows us to trace out the productivity levels for each month just before and after the treatment.

$$
\begin{aligned}
y_{ijt} = \alpha_{ij} + \beta_1 X_{ijt} + \beta_2 X_{ijt}^2 + \gamma M_t + \delta_0 m_{jT-2} + \delta_1 m_{jT-1} + \delta_2 m_{jT} + \delta_3 m_{jT+1} + \delta_4 m_{jT+2} + \delta_5 m_{jT+3} \\
+ \delta_6 m_{jT+4} + \delta_7 m_{jT+5} + \delta_8 m_{jT+6} + \delta_9 m_{jT+7} + \delta_{10} m_{jT+8} + \delta_{11} m_{jT+9} + \mu_{ijt} \\
where\, \mu_{ijt} = \rho \mu_{ijt-1} + \varepsilon_{ijt}
\end{aligned} \tag{3}
$$

m_{jT-2} is a dummy variable equal to 1 for the month that is two months prior to the treatment and 0 for all other months (due to the different treatment dates, this will correspond to different months across institutions)

m_{jT-1} is a dummy variable equal to 1 for the month that is one month prior to the treatment and 0 for all other months

m_{jT} is a dummy variable equal to 1 for the month in which the treatment was implemented and 0 for all other months

m_{jT+i} is a dummy variable equal to 1 for month corresponding to i months after the treatment effect and 0 for all other months; where i=1-9

5.5 Estimation results of timing of average effects

Table 5: Timing of Average Treatment Effects
(t-statistics are in parentheses)

	Nat. log of value of outstanding portfolio	**Nat. log of number of clients**	**Nat. log of average loan size**	**Delinquency rate**
Tenure (in months)	-.0535 (-5.95)	-.0703 (-8.85)	.0169 (8.84	.0044 (3.69)
Tenure squared	.0010 (5.96)	.0012 (7.77)	-.0002 (-4.57)	-.0001 (-3.09)
Monthly dummy variables	Yes	Yes	Yes	Yes
m_{T-2}	-.0113 (-1.15)	-.0194 (-2.48)	.0035 (0.62)	.0030 (1.63)
m_{T-1}	-.0346 (-2.57)	-.0353 (-3.28)	-.0067 (-0.91)	.0003 (0.11)
m_{T}	.0028 (0.17)	-.0071 (-0.54)	-.0004 (-0.05)	-.0044 (-1.47)
m_{T+1}	.0241 (1.23)	.0171 (1.09)	-.0067 (-0.68)	-.0072 (-2.02)
m_{T+2}	.05 (2.27)	.0344 (1.94)	-.0006 (-0.06)	-.0077 (-1.91)
m_{T+3}	.0537 (2.22)	.0438 (2.25)	-.0089 (-0.76)	-.0073 (-1.65)
m_{T+4}	.0703 (2.68)	.0578 (2.73)	-.0077 (-0.62)	-.0114 (-2.42)
m_{T+5}	.0727 (2.63)	.0721 (3.24)	-.0202 (-1.56)	-.0095 (-1.92)
m_{T+6}	.08 (2.73)	.0750 (3.17)	-.0166 (-1.23)	-.0168 (-3.20)
m_{T-7}	.0677 (2.17)	.0601 (2.38)	-.0130 (-0.90)	-.0207 (-3.71)
m_{T-8}	.0468 (1.44)	0.054 (2.04)	-.0264 (-1.79)	-.0184 (-3.20)
Coef. of autocorrelation	.86	.87	.67	.81
# of observations	4398	4398	4398	4401
# of credit officers	310	310	310	310
Modified Bhargava et al. statistic	.30	.28	.67	.38
Baltagi-Wu test stat.	.68	.68	.90	.60
Adj. R2 within	0.04	0.04	0.06	0.02
between	0.37	0.34	0.25	0.02
overall	0.38	0.42	0.21	0.04

It is interesting to note that the coefficients for the two months immediately prior to the treatment period were significant and negative for the value of outstanding portfolio and number of clients indicators. Compared to the previous months, the productivity was lower for the two months prior to the treatment. A sensitivity check (including dummy variables for the third and fourth months prior to treatment) shows that this dip does not extend before this two month dip. There seems to be some endogeneity in the choice to implement the treatment effect. If so, a possible story is that the managers were experiencing lower performance and/or lower motivation of their credit officers and decided to increase the incentives to increase output. Considering that it generally takes 1-2 months to plan, revise, and announce a change in the incentive scheme, this story seems even more plausible.

The direction of this potential bias (the significantly negative performance in the two months leading up to the treatment effect) is not entirely clear. If it represents a very short-term exogenous dip, then our analysis would be over-stating the effects of the treatment (our treatment effect would be capturing part of the natural recovery of the dip). On the other hand, if the negative period is caused by a longer term state of stagnation and poor productivity, then our true treatment effect might be stronger than our original estimates.

When examining the effect on outstanding portfolio, we see that the treatment effect occurs quite rapidly, beginning even within the first month and reaching full effect after about 7 months. The total accumulated effect is quite impressive, about 7% over the pretreatment period and about a 10% increase over the pretreatment dip. There is a similar pattern regarding the timing and magnitude of the treatment effect on the number of current clients.

We do not see an average overall effect on the average loan size. The effect of the treatment on delinquency rate is quite dramatic. Within two months, we see a .7% drop in the delinquency rate and by the eighth month, we see a drop of almost 2%.

5.6 Permutation of specification equation: Microfinance Sector control variable

All of the previous regression specifications controlled for seasonality through the use of 11 dummy variables for months of the year (Feb, Mar, etc.). We have also experimented with an alternative control: an indicator of the performance of the Peruvian microfinance industry as a whole. We have indicators for: total value of outstanding loan portfolio, average delinquency rate, and total number of credit officers for regulated MFIs in Peru from the Superintendent of Banking and Insurance (SBS) of Peru for the period of the study.[18]

This indicator has an advantage over the month dummies in that it can also capture time trends and macroeconomic shocks. However, it was only available quarterly for the first 12 months of the study period, and then monthly afterwards. Also, since the indicator reflects total industry levels, it only corresponds indirectly to our credit officer level data. For example, if an institution hired 20 new credit officers in a month, this statistic would show that the average portfolio per credit officer suddenly decreased. Since we use fixed effects at the credit officer level, our results would not be affected in this manner.

In the interest of brevity, we will not display the regression results using the industry average control statistics. In general they performed similarly (but not quite as well) in terms of

[18] There are actually several classes of regulated financial institutions in Peru, the indicator we used was for the class most similar to the MFIs in our sample, called "EDPYMES," which tend to be former NGOs that are now regulated.

explanatory power, and the magnitude and nature of the treatment effects were robust to this alternative indicator. When both the month dummies and the industry average control statistic are included, some of the months are dropped due to multi-colinearity (because the industry average statistic was only available quarterly for the first year).

5.7 *Permutation of specification equation: Separate regressions by MFI*

For each of the regressions, we have pooled all credit officers into the same regression instead of running separate firm-specific regressions. One key difference between the pooled and firm-specific regressions is that the pooled regression assumes that tenure, eligibility, and seasonality have the same effect across institutions. The firm-specific regressions are more efficient if these underlying equations are very different across institutions. However, we lose a large number of observations that could help detect treatment effects if they are similar in structure across institutions.

All of the specifications were also run by firm and most of the results presented above are similar to the results obtained from firm-specific regressions.[19] In order to save space and time, we will not present all of the regression results, but will highlight any differences in the results. Firstly, MFI 5 was dropped due to collinearity in the firm-specific regression; this is primarily due to the fact that there were much fewer months after the treatment effect for this MFI.

In comparing the pooled and firm-specific approaches, we see that there were some differences with regard to MFI 2. The treatment effects (or lack of) for institutions 1, 3, and 4 remained relatively unchanged between the two approaches. For MFI 2, we now detect a significant treatment effect (whereas we did not under the pooled approach) for the loan portfolio (at the .1 level of confidence), and number of clients.

In some of the firm specific estimations, we also included branch-treatment interaction dummy variables. We find a significant and large differential effect of the treatment across branches, especially for MFIs 1 and 3. This confirms our prediction that local market conditions are important determinants of response to the incentives.

6 Estimating heterogeneous treatment effects

6.1 Role of contract non-linearities and initial productivity levels

We have predicted that credit officers who are significantly below a minimum standard will not have any incentive to respond to an increase in the incentive payments. Generally, MFIs have minimum standards for delinquency rate and value of outstanding portfolio or number of clients. The delinquency rate is the indicator that is most frequently binding, especially for credit officers with at least five or six months of tenure. The following table shows the distribution of credit officers by range of delinquency rate in the month prior to the treatment. According to our prediction, it appears that between a third and a half of the credit officers in each institution will not be affected by the increase in the intensity of the incentive payments.

[19] We could have included them in the pooled sample, but comparing branch effects across institutions would have held less meaning than comparing branch effects within an institution.

Table 6: Percentage of Credit Officers by Range of Delinquency Rate
(corresponding to the month prior to the treatment effect)

Delinquency Rate	MFI1	MFI2	MFI3	MFI4	MFI5
<8%	54.3%	42.8%	27.4%	35.2%	35.1%
8-12%	9.4%	21.4%	13.1%	29.6%	18.9%
>12%	36.2%	35.7%	56.5%	42.6%	45.9%

6.2 Estimation results of treatment effects by initial productivity levels

We can estimate the same regression specification (equation 2) as before but now we will run it separately for credit officers who have an initial delinquency rate: below 8%, between 8 and 12%, and greater than 12%. Table 7 presents only the estimated coefficient on treatment effect for the three regressions (<8%, 8-12%, >12% initial delinquency rate) for each of the four performance indicators, after controlling for seasonality and tenure..

Table 7: The Importance of Initial Delinquency Rate on the Treatment Effect Across Indicators
(t-statistics are in parentheses)

Coefficient on Treatment effect	<8%	8-12%	>12%
Natural log of portfolio	.057 (3.94)	.033 (1.94)	.017 (0.75)
Natural log of # of clients	.040 (3.48)	.025 (1.85)	.021 (1.12)
Natural log of avg. loan size	.016 (2.01)	.005 (0.53)	-.013 (-1.00)
Delinquency rate	-.0036 (-2.12)	-.0039 (-1.54)	-1.43 (-2.35)
# of obs. # of credit officers	2231 129	900 49	1325 136

We see that the portfolio increased by approximately 5.7% following treatment among the credit officers that had a delinquency rate below 8%. Meanwhile, credit officers who did not meet the cut-off criteria of 8%, but had a delinquency rate under 12% increased their outstanding portfolio by an average of 3.3%. Credit officers who had an initial delinquency rate above 12% did not significantly increase their outstanding portfolio following the treatment.

We see a similar pattern of how credit officer response to the treatment varies according to the initial level of delinquency rate in terms of number of clients. In other words, the treatment effect had resulted in no significant increase on outstanding portfolio or number of clients among the more than 40% of the credit officers who had an initial delinquency rate above 12%..

We see that although the differential effect across credit officers is not as pronounced for the indicator for average loan size, it is still present and significant.

Finally, we see that credit officers with the highest initial delinquency rate have experienced the largest and most significant reduction in the delinquency rate following the treatment. This could imply that the credit officers who are above the cut-off are working hard to become eligible to receive incentives. However, the results do not support this hypothesis since we would expect there to be an even greater incentive effect among the 8-12% group than among the >12% group.

6.3 Estimation results of treatment effects by rural/urban context

We have predicted that credit officers who operate in more difficult areas are less likely to respond to incentives. In the previous section we have shown how initial delinquency rate can help to determine whether a credit officer responds to the treatment. We will try to put a little more structure on this concept by testing for heterogeneous treatment effects in urban vs. rural areas. Of the 31 branch offices in the dataset, 10 of the branches operate in mixed urban/rural areas while 21 of the branches operate only in urban areas.

First, we note that there are noticeable differences in productivity between the rural and urban areas with regard to average productivity indicators. The average delinquency rate among the urban/rural branches is 10.7% while only 7.3% in the urban branches. Similarly, credit officers in the urban/rural mixed areas have an average of 178 clients while those in the urban areas have 202 clients on average.

Again we estimate our standard fixed effects regression specification but run it separately for credit officers in rural/urban branches and for credit officers in urban branches. As before, Table 8 presents only the estimated coefficient on treatment effect for the separate regressions for each of the four performance indicators, after controlling for seasonality and tenure.

Table 8: Heterogeneous treatment effects across urban vs. rural contexts
(t-statistics are in parentheses)

Coefficient on Treatment effect	**Urban**	**Rural***
Natural log of portfolio	.045 (4.25)	.036 (1.31)
Natural log of # of clients	.034 (3.84)	.027 (1.33)
Natural log of avg. loan size	.009 (1.43)	.006 (0.39)
Delinquency rate	-.005 (-2.95)	-.009 (-1.47)
# of obs. # of credit officers	3359 235	1042 75

*The "rural" branches are actually branches that serve both urban and rural areas in approximately equal proportions.

Although we see some evidence supporting a differential treatment effect depending upon whether the credit officer operates in a rural or urban setting, our results are not entirely conclusive since our sample size for the rural credit officers is considerably smaller.

7. Discussion and Conclusions

In this paper, we have estimated the magnitude and nature of the response of credit officers to an increase in the power of an incentive scheme. As other empirical studies on the impact of incentives for employees have shown, we have found that incentives do matter. However, while most of these previous studies have focused on estimating a single average productivity impact, we have discovered some interesting heterogeneity in the incentive effects across indicators, institutions, credit officers, and contexts.

7.1 Average treatment effects

Credit officers significantly increased the value of their outstanding portfolio and number of clients while reducing their delinquency rate within months of the change in the incentive scheme. Estimations of the magnitude of increases to outstanding portfolio and number of clients were between 4% and 8% (after controlling for tenure and seasonality), which could be encouraging to practitioners. We also found a significant decrease in the delinquency rate of up to 2%. The productivity effects occurred relatively rapidly, beginning within one to two months of the change in the scheme and continuing until the full effect is attained within about seven or eight months.

7.2 Effects across multiple dimensions

Although we saw no negative substitution effect between the two primary tasks of increasing loan portfolio and maintaining a low delinquency rate, this finding should be considered within the context of our study. Each of the five institutions already had a multi-dimensional incentive scheme, even if it was very weak-powered. Our treatment effect was essentially to increase the power of this contract equally across all tasks. Substitution between tasks could still occur due to differences in marginal costs and marginal benefits of increasing effort across different tasks, but we did not find this to be the case. There have been several anecdotal accounts of institutions that indeed suffered very costly substitutions between portfolio and delinquency following the implementation of a *new* incentive scheme, presumably because they did not correctly assign weights between tasks or establish appropriate minimum cut-off levels for performance in each task.

There is another concern expressed by donor agencies and managers of some MFIs that incentive schemes might result in a shift from poor clients to non-poor clients. We do not have data on the wealth level of clients and can not completely address the concern about a shift towards non-poor clients. However, there is a correlation between average loan size and the wealth level of clients. Institutions and credit officers authorize loan amounts for clients based upon their capacity to repay and wealthier clients are allowed to borrow larger amounts of money. Our analysis shows that in the two non-profit MFIs, the average loan size increased by 4.5% in one and by 8% in the other. Interviews with credit officers confirm that there is a slightly greater focus on wealthier clients in response to the incentives. However, these changes tend to be subtle and on the margin as opposed to an obvious and rapid shift in clientele.

We are unable to identify or measure any possible long-term substitution effects away from quality. Interviews with credit officers and managers have reported a slight decrease in the quality of attention to clients as credit officers become more focused upon output indicators. Individual actions can have significant externalities for the institution that would not be captured by our data or reflected in the credit officer's own incentives. For example, if a credit officer treats potential clients in an increasingly brusque manner to lower his processing time for new clients, a percentage of potential clients might be turned off and will never return for another loan from the institution. Similarly, a credit officer might decide to ignore certain delinquent clients if their outstanding amounts are very low (i.e. he is maximizing his benefit from incentives minus cost of effort), however, this could produce a negative externality where the reputation of the institution as an enforcer of all delinquent loans is undermined.

7.3Effects across institutions

It is interesting to point out that most of the increase in productivity was experienced by the two non-profit institutions in our sample. This seems to be contrary to the common perception that employees in non-profit institutions have higher levels of intrinsic motivation and might not respond as much to monetary incentives. Since we only have a total of five institutions, we have to be careful not to read too much into this finding. The qualitative component of the research however suggests that the employees in the non-profit institutions had much more room to improve; prior to the treatment they were generally less motivated.

7.4 Effects across individuals and contexts

Perhaps one of the most surprising findings is that a large proportion of credit officers are not affected by the increase in the power of the incentive scheme. This is primarily due to the non-linear design of the incentive contract. About 40% of the credit officers were so far below the cut-off standards stipulated in the incentive contract, that they were not motivated by the incentive scheme either before or after the increase in incentive intensity. Because of this, our estimated average treatment effect greatly underestimates the incentive effect among credit officers who do meet the minimum standards.

The principal concern and critique of the staff incentive policies expressed by the credit officers during the interviews was the fact that the incentive contract is a uniform one-size-fits-all contract for all employees regardless of where they are assigned to work. Credit officers working in more difficult, rural, or poor areas have the same benchmarks and parameters as credit officers working in the most dynamic areas. Although our data found a significant difference between branches in urban areas and those that work in mixed urban/rural areas, the data was not rich enough to fully document these differences.

There are many real world situations where local market conditions greatly affect the productivity of the workers but are not sufficiently distinguishable or exogenous to contract upon. The application of a uniform one-size-fits-all contract will not necessarily (perhaps even rarely) provide incentives for all employees to increase effort and output. This diversity of conditions faced by employees is a potential problem for virtually all incentive- or commission-based schemes, but has yet to be addressed by the theoretical or empirical literature. The shift of a waiter, shift of a taxi driver, geographical area of a salesman or manager of a chain restaurant, all significantly influence the opportunity to earn incentives/commissions/tips. Many industries handle this fairness problem by giving the choice of best areas/shifts to those with more tenure (as a form of promotion incentive). However, this is very difficult to do for credit officers and employees in several industries: there are often very high costs associated with transferring employees who have highly specialized knowledge of local markets.

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ANNEX: Analysis of Staff Attrition

Analysis of Staff Attrition by Quartile of Productivity

Dummy variable=1 for employees' last full month of employment, 0 for all other months that they are employed. The mean represents the percentage of attrition (percentage of employees leaving voluntarily or involuntarily) per quartile of outstanding portfolio. The column T=0 corresponds to months prior to the treatment effect and column T=1 corresponds to months following the treatment effect.

Institution 1

T=0				T=1			T test difference	
Quartile	Mean	Std. Dev	Obs.	Mean	Std. Dev	Obs.	Mean	P value
1 (Lowest)	0.74%	.0861	269	2.86%	.1670	210	2.11%	0.073
2	2.31%	.1504	260	3.40%	.1816	206	1.09%	0.479
3	2.27%	.1493	264	0	0	208	-2.27%	0.029
4 (Highest)	3.49%	.1838	258	5.42%	.2269	203	1.93%	0.314
	1.29%	.1130	1778	1.57%	.1245	1524	0.28%	0.497

Institution 2

T=0				T=1			T test difference	
Quartile	Mean	Std. Dev	Obs.	Mean	Std. Dev	Obs.	Mean	P value
1 (Lowest)	0	0	33	0	0	39	0%	
2	4.35%	.2085	23	3.03%	.1741	33	-1.312%	0.798
3	0	0	32	0	0	39	0%	
4 (Highest)	4.55%	.2132	22	0	0	26	-4.54%	0.282
	1.09%	.1045	182	0.55%	.0741	182	-0.55%	0.563

Institution 3

T=0				T=1			T test difference	
Quartile	Mean	Std. Dev	Obs.	Mean	Std. Dev	Obs.	Mean	P value
1 (Lowest)	1.47%	.1208	136	4.52%	.2083	155	-3.05%	0.135
2	1.49%	.1217	134	2.61%	.1601	153	-1.12%	0.509
3	0.75%	.0864	134	0	0	153	0.75%	0.286
4 (Highest)	0	0	128	0	0	151	0%	
	0.35%	.0591	1428	1.46%	.1198	756	1.10%	.004

Institution 4

T=0				T=1			T test difference	
Quartile	Mean	Std. Dev	Obs.	Mean	Std. Dev	Obs.	Mean	P value
1 (Lowest)	2..24%	.1485	134	3.13%	.1749	96	0.89%	0.679
2	0.77%	.0877	130	0	0	90	-0.77%	0.407
3	1.49%	.1217	134	1.05%	.10260	95	-0.44%	0.774
4 (Highest)	0.83%	.0909	121	0	0	87	-0.83%	0.398
	0.76%	.0870	918	1.03%	.1010	486	0.52%	0.606

Institution 5

T=0				T=1			T test difference	
Quartile	Mean	Std. Dev	Obs.	Mean	Std. Dev	Obs.	Mean	P value
1 (Lowest)	1.43%	.1195	70	1.85%	.1361	54	0.42%	0.854
2	0	0	70	0	0	49	0%	
3	4.29%	.2040	70	0	0	49	-4.29%	0.145
4 (Highest)	4.48%	.2084	67	0	0	49	-4.48%	0.136
	0.99%	.0994	703	0.39%	.0621	259	-0.66%	0.356