Incentivizing Inclusion: Experimental Evidence on Lending to Women-Led Firms in Vietnam

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March 26, 2026

ABSTRACT

We study how financial incentives affect worker performance in complex, high-stakes tasks, focusing on credit allocation to underserved women-owned or -led small and medium enterprise (WSME) borrowers. In a randomized field experiment with a large commercial bank in Vietnam, 50 branches are assigned to a monthly multi-category contest, piece-rate incentives, or a control group, for six months. The intervention targets lending to entrepreneurs operating larger, growth-oriented firms, as we observe USD $34 million in lending to new WSME borrowers across the treatment and control groups. The treatments generate 40 percent more lending to new WSMEs, with the contest generating larger effects of 58 percent. Treatment effects are stronger among female loan officers, particularly under the contest, and in urban branches. We find no evidence of strategic responses or trade-offs along other margins: incentives do not reduce loan size, crowd out lending to other borrowers, or increase delinquency. The results provide evidence of a market failure in credit allocation to women-owned or -led firms: incentives induce large increases in lending without offsetting costs, while highlighting the role of competitive incentives in shaping effort in multidimensional tasks.

Keywords: WSME finance, banking, incentive design, financial inclusion, randomized controlled trial, Vietnam

JEL codes: O16, G21, J16, O12

This research was supported by the Women's Entrepreneurs Finance Initiative (We-Fi) and Asian Development Bank (ADB) Regional Technical Assistance Promoting Transformative Gender Equality Agenda in Asia and the Pacific. We thank Don Lambert, Keiko Nowacka, Maria Pateguana, and Que N. Do for their support to the study. Research assistance was provided by Giang Tran, Huong Giang Nguyen, Frederic Cochinard, Sophia Cyna, and William Greenland. Dao Gia Hung of Vietnam Prosperity Joint Stock Commercial Bank (VP Bank) and staff in the Small and Medium Enterprise and Enterprise Data and Analytics divisions, particularly Nguyen Canh Hung, supported implementation. This working paper is based on Asian Development Bank Economics Working Paper Series paper #831. Ethical approval for the study has been provided by Rutgers University, Human Research Protection Program (HRPP), Institutional Review Board (IRB),

protocol Pro2023000766, granted on 5 June 2023. This study is pre-registered on the American Economic Association Randomized Controlled Trial Registry, AEARCTR-0011576.

1 INTRODUCTION

It has been estimated that micro, small, and medium-sized enterprises (MSMEs) in emerging markets face a $5.2 trillion annual financing gap, with $1.5 trillion attributed to women entrepreneurs (Bruhn et al. 2017). Although the aggregate gap may seem smaller for women-owned or -led small and medium-sized enterprises (WSMEs), the gap is much higher in relation to the market share of these enterprises. Lending institutions often treat WSMEs less favorably than men-led or -owned SMEs. Women entrepreneurs were estimated in a recent meta-analysis of the literature to have 1.26 standard deviations higher loan rejection rates and 0.087 standard deviations higher interest rates than male entrepreneurs (Malmström et al. 2023). This gender gap in WSME finance is more pronounced in regions that perform worse on the Global Gender Gap Index, such as Asia (Chundakkadan and Sasidharan 2022).

In Vietnam, WSMEs have been estimated to face a $1.19 billion annual financing gap (IFC 2017). A study on the banking industry showed that only 37% of WSMEs had received bank loans in the preceding 2 years, compared to 47% of men-owned SMEs, and even when they qualified, WSMEs tended to receive less than what they asked for and in lower amounts than men (IFC 2017). Furthermore, the study showed that industry stakeholders widely held false beliefs, such as that women entrepreneurs were generally more likely to default on loans.

Increasing access to finance for WSMEs has the potential to reduce credit constraints and promote firm growth, which can improve outcomes for employees and consumers, and empower women entrepreneurs. Given the evidence that misallocation of capital is particularly prevalent in emerging economies (Hsieh and Klenow 2009), with particularly large distortions for women entrepreneurs (Chiplunkar and Goldberg 2024), redirecting it toward WSMEs could also promote economic growth through targeting an underserved market segment. Finally, individual banks that lead in overcoming this inefficiency in lending markets could enjoy a competitive advantage.

Lending agents are the primary bank representatives who reach out to prospective new borrowers.[1] But how can these agents be incentivized to increase their effort toward a bank's strategic goal of increasing lending to WSMEs? A large literature has already broadly examined different incentive schemes for motivating employee productivity and performance (as reviewed by, e.g., Baker, Jensen, and Murphy 1988; Prendergast 1999). However, existing work does not yet provide clear guidance on which incentive design would be most effective in our context, which involves seeking to address gender inequality in access to bank loans in a developing country bank.

Optimizing worker incentives is a key element in enhancing worker productivity and organizational performance. The choice of pay structure has been shown to relate to improved worker performance and organizational outcomes (e.g., Oyer 1998), in part through fostering engagement and motivation (Fang and Gerhart 2012). An important strand of the literature on pay incentives focuses on performance pay, where a worker's pay depends directly on their performance. A key decision in this vein is between performance pay schemes like piece rates,

[1] We use the term "lending agent" equivalently to "loan officer."

where pay depends only on one's own performance, and incentive schemes based on relative performance, such as contests and tournaments. Seminal theoretical contributions by Lazear and Rosen (1981) and Nalebuff and Stiglitz (1983) suggest that, while piece rates may be optimal for repetitive and closed-ended tasks, open-ended and complex tasks may be better motivated through competitive incentive mechanisms like rank-order tournaments. However, there is still scant empirical evidence from high-stakes field experimental settings with workers completing complex open-ended tasks to corroborate this theoretical prediction.

In this study, we measure the impact of real-stakes financial incentives that explicitly reward recruitment of new WSME borrowers by the lending agents of a large commercial bank in Vietnam. Specifically, we implement a randomized controlled trial (RCT) that compares the impact of (i) bonus incentives from a monthly multi-category contest for the highest number of new WSME borrowers (henceforth the contest treatment), (ii) bonus incentives from a piece-rate incentive per new WSME loan (henceforth the piece-rate treatment), and (iii) a control.[2] The contest is designed to be more inclusive than a simple "winner-take-all" contest, by awarding prizes not just to top overall performers, but also the best-performing new agents (agents hired in the past 12 months), and agents with little recent success in WSME lending (agents with at least 12 months of experience and no more than two WSME loans sold in the previous 12 months). The piece-rate incentive pays agents a fixed amount per new WSME loan. The two programs' budgets were calibrated to make the funds available in each treatment arm as equal as possible.

Our two treatments represent two levels of between-colleague competition based on pecuniary incentives, with the contest treatment representing stronger competition and the piece-rate treatment representing weaker competition. To isolate the effect of structuring incentives at these two different levels of competition from the benefits of social recognition, information disclosure about lending performance is balanced between the two treatment arms. In particular, all participants receive mid-month updates on the ranking of WSME lending performance within their treatment arms. Furthermore, managers in *both* treatment arms are eligible for identical sets of competitive quarterly awards for top branch-level numbers of new WSME borrowers in both treatment arms. A larger number of branches can win a publicly-announced award, which the branch manager would typically share with branch staff. A couple branch managers can also win a bonus that is only announced to the winning managers, privately. These incentives are calibrated to induce managers' support for the program without providing unduly large incentives. All of this is meant to keep the focus of our analysis on the comparison of differing levels of inter-agent competition between our two treatments.

Our design randomizes assignment of the two treatments and control across 50 branches, which are stratified into two groups: 13 larger branches based in urban commercial centers (henceforth referred to as urban branches, or Group 1) and 37 smaller branches spread across

[2] In our partner bank, on average, agents receive about 50% of income in terms of fixed salary; about 25% of income from core Key Performance Indicators (e.g., portfolio growth and quality), which are not linked to clients' gender; and about 25% from special bonus and incentive programs, such as ours, though none of these other programs targeted WSMEs during our study period. Hence, our intervention is not an overwhelming portion of agents' incomes, and agents continue to have incentives to pursue objectives relevant to the bank, e.g., portfolio quality.

the rest of the country (henceforth referred to as provincial branches, or Group 2).[3] In the contest treatment, all eligible lending agents in each group are eligible for that group's awards, e.g., 4 of 13 urban branches in Group 1 are assigned to the contest treatment, meaning that all agents within these 4 branches compete with each other for the monthly awards. Since there is significant heterogeneity between the provincial branches, to level the playing field we adjust contest scores in Group 2 by a provincial index that we create based on the proportion of women entrepreneurs in the branch's province.[4]

We aim to mitigate some of the downsides of competition within winner-take-all contests through three aspects of our contest design. First, our multi-category contest design involves three award categories, allowing lending agents with less previous experience and success in bringing in WSME borrowers to compete against similar agents. This should reduce discouragement effects from winner-take-all contests with heterogeneous participants (Baye, Kovenock, and Vries 1993; Baik 1994; Gradstein 1995) Second, competition is between agents across multiple branches, not just a focal agent's own branch, which may reduce concerns that the contest could reduce cooperation between staff within branches, or induce negative social pressure (e.g., as in Bandiera, Barankay, and Rasul 2005). Third, we attempt to calibrate the award amounts and the number of awards to not lead to excessive distortions in pay. For example, one might worry that the incentives induce lending agents to unduly lend to women (over men), or to lend to excessively risky female borrowers. Dividing the contest by months rather than longer time periods also keeps the stakes lower and keeps re-engaging participants by restarting the count from zero in each month.

The overall intervention period that we focus on in this paper is 6 months (February 2024 to July 2024). This followed a previous 6-month pilot phase (July to December 2023), during which the research team and the partner commercial bank worked through numerous implementation challenges. Outcomes are measured through administrative data from the partner bank.

Analysis is conducted at the lending agent level. Our main outcome is the number of new WSME borrowing clients each month, specifically for secured (i.e., collateralized), unsecured, and overdraft loans.[5]

Our results show that financial incentives for lending agents substantially increased lending to WSMEs. On average, exposure to any incentive program raised the number of new WSME loans issued per agent-month by roughly 40% relative to the control mean, with larger gains

[3] Technically, our study is focused exclusively on our partner bank's lending to its relatively smaller category of SMEs. In particular, the bank divides SMEs between those at and above D60 billion (about $2.4 million) in annual revenue and those below this cutoff. Our focus is firms in the below category. The upper limit on collateralized loan sizes for this category of SMEs is D25 billion (about $1 million), but it ultimately depends on what specific collateral they provide. In practice, the maximum collateralized loan size for these firms is D5 billion (about $200,000), while the average collateralized loans for these firms are around D2 billion (about $80,000). The upper limit on uncollateralized loans (i.e., cash flow-based lending), in turn, is D1.5 billion (about $60,000), while the average uncollateralized loans are D300–D500 million (about $12,000–$20,000). Ten of our Group 1 branches engage exclusively in lending to these smaller SMEs. The 3 others in Group 1 and all 37 in Group 2 also engage in lending to the larger category of SMEs.

[4] The index is calculated based on the 2020 Vietnam Enterprise Census produced by the Government of Vietnam's General Statistics Office. This index is also used to adjust numbers for manager awards in Group 2.

[5] We exclude other credit products such as credit cards from eligibility.

in urban branches where economic activity and lending potential are greater. Both contest and piece-rate incentives increased new client acquisition, although the contest generated about twice the improvement and was statistically significant. These results suggest that incentive pay can meaningfully improve inclusion outcomes in commercial banking, especially in markets where lending agents face weaker intrinsic motivation or lower opportunity.

In spite of the increased WSME lending activity induced by our incentives, we find little evidence of adverse side effects. The increase in loan numbers was not accompanied by reductions in average loan size, declines in loan quality, or crowding-out of other lending activity. On the contrary, there are hints of positive spillovers in lending to male entrepreneurs in the same portfolio. Finally, we document that female lending agents respond at least as strongly as, and often more strongly than, their male counterparts—particularly under the contest scheme for number of loans, and piece rates for volume of loans—contrary to prior findings that women underperform in competitive settings. Together, the evidence indicates that well-designed incentive pay can enhance financial inclusion without compromising portfolio quality or fairness, and that gender composition and market context shape the effectiveness of incentive mechanisms in important ways.

The study makes at least four contributions to the literature.

First, the study contributes to a broader literature in economics on optimal incentive contract design and performance pay, and particularly the question of whether piece rate-based performance pay or a contest mechanism would perform better. Theoretical literature such as Lazear and Rosen (1981) and Nalebuff and Stiglitz (1983), shows that piece-rate incentives tend to be more effective for repetitive, closed-ended tasks, where there is a relatively tight connection between effort and output, while competitive incentives such as contests and tournaments can be more effective when there is greater task autonomy, uncertainty, and asymmetric information. A large lab experimental literature (e.g., early studies such as Bull, Schotter, and Weigelt (1987), as reviewed by Charness and Kuhn (2011) and Dechenaux, Kovenock, and Sheremeta (2015)) tends to corroborate these theoretical predictions. However, there is less evidence from real-stakes field settings, with much of the existing work from university classroom and lab settings (Dechenaux, Kovenock, and Sheremeta 2015). Existing work from field experiments outside the university has been conducted in the context of repetitive tasks such as fruit picking in the UK (Bandiera, Barankay, and Rasul 2005) and a manufacturing assembly line in India (Breza, Kaur, and Shamdasani 2018). Consistent with the theoretical literature, both studies find that piece rates tend to outperform relative or rank-based incentives, in part because of adverse social interaction mechanisms such as negative social pressure, and reduced cooperation, respectively. Our study contributes to this literature by providing real-stakes, field experimental evidence on two different incentive mechanisms regarding a relatively high-stakes, uncertain, autonomous task.

Second, the study contributes to the literature on optimal incentive pay for lending agents in financial institutions. While there is a large literature on the pay of senior management, and particularly CEOs (Frydman and Jenter 2010), a smaller literature explores incentives for frontline

staff such as lending agents. This literature focuses on how badly designed incentives can lead to suboptimal outcomes in advanced and emerging economies. Literature using European and US data shows how performance pay can lead to distortions such as making lending agents over-attentive to incentive targets and ignoring activities in the interest of the bank (Behr et al. 2020; Agarwal and Ben-David 2014, Efing et al. 2015). There is also a small field experimental literature on performance pay in this context. Working with a US bank, Agarwal and Ben-David (2018) show that incentivizing originated loan volume causes a large increase in origination, but also in default, seemingly because greater weight is put on hard rather than soft information. Berg, Puri, and Rocholl (2020) echo this finding. In the emerging market setting, Cole, Kanz, and Klapper (2015) conduct a large framed field experiment in an Indian bank that varies the extent of high-powered incentives, limited liability, and deferred compensation for small business loan assessment. They find that limited liability and deferred compensation can offset the beneficial effects of high-powered incentives on screening effort and lending profitability. Rigol and Roth (2021) show how misaligned incentives for microfinance lending agents induce them to prevent their best clients from "graduating" to larger loan amounts. An emerging strand of literature also focuses on informational concerns. For example, Qian, Strahan, and Yang (2015) leverage quasi-experimental variation from a trade agreement to show how empowering lending agents can lead to beneficial lending outcomes in a Chinese bank, while Deserranno, León-Ciliotta, and Witoelar (2025) conduct a field experiment with a large Indonesian bank, showing how informing clients about performance pay of banking agents can temper demand for financial products. Our study contributes to this literature by providing new real-stakes, field experimental evidence on incentives for lending to larger, growth-oriented enterprises. It does so by comparing two performance pay mechanisms that are widely used in banks, particularly in emerging markets.

Third, the study contributes to the emerging literature on gender and finance. One strand of this literature focuses on the gender of the borrower. An earlier literature on capital shocks for microenterprises in developing countries (e.g., Mel, McKenzie, and Woodruff 2008) purports to show that women entrepreneurs have lower returns to capital. However, Bernhardt et al. (2019) reconcile this puzzle by reanalyzing the data from a number of previous experimental studies, showing that women entrepreneurs often pass through capital from microloans and grants to other (typically male-owned) household enterprises. Other literature attempts to quantify discrimination toward women entrepreneurs. Hebert (Forthcoming) uses administrative data on the population of startups in France and shows that women-founded startups are 18% less likely to receive external equity including venture capital, overall. However, there appears to be heterogeneity by sector: the gender funding gap reverses in women-dominated sectors, suggesting the possibility of context-dependent stereotypes on the part of lending agents. In the emerging economy setting, Brock and De Haas (2023) conduct a lab-in-field experiment with Turkish lending agents, presenting them with loan applications based on numbers from real loan applications, where only the gender of the applicant is randomly varied. While provisional loan approval rates are the same for male and female applicants, lending agents are 30% more likely to make approval conditional on the

presence of a guarantor when the applicant is female. This discrimination is concentrated among young, inexperienced, and gender-biased lending agents. Our study contributes to the borrower-focused literature on gender in lending both by evaluating an organizational intervention in a bank that aims to increase lending to growth-oriented, women entrepreneurs and by studying heterogeneity in lending outcomes based on the gender of lending agents—each in the context of a real-stakes field experiment.

Finally, there is less evidence on the role of lending agent gender. Papers such as Drexler and Schoar (2014) and Fisman, Paravisini, and Vig (2017) show how relationship-specific knowledge and cultural affiliation between lending agents and their clients can matter for lending outcomes, generally in positive ways, though they do not particularly focus on the dimension of gender. Our study contributes to the scant evidence on lending agent gender by analyzing heterogeneity in treatment impacts along the dimension of lending agent gender. A large literature shows women tend to be more likely than men to avoid competition when they have the option, and their performance tends to be stable or decline under competition, while men's performance is more likely to improve (Niederle and Vesterlund 2011). At the same time, female lending agents may have a competitive advantage in relating to WSME clients, which makes them better placed to respond to either type of incentive. We provide some of the first evidence from a high-stakes, field setting, that shows women outperforming men, particularly under explicitly competitive incentives.

In Section 2, we present the context of the study, our intervention, and our primary hypotheses, which is followed by a section presenting our RCT design and reporting on balance checks and other internal validity checks, and our empirical methodology (Section 3). We present results in Section 4, while Section 5 concludes. Additional results and materials are included in the Appendices.

2 CONTEXT, INTERVENTION, AND HYPOTHESES

In this section, we briefly review the context of SME lending, and lending specifically for women entrepreneurs, in Vietnam. We then present the interventions that we test in this paper, which are intended to overcome constraints to WSME lending. Finally, we present our hypotheses about the impacts of these interventions.

2.1 Context: Bank Lending and Women Entrepreneurs in Vietnam

Vietnam has been one of the world's fastest-growing economies in recent decades, driven by inward foreign direct investment and export promotion that followed the end of central planning in the late 1980s and the advent of meaningful Doi Moi reforms in the early 1990s (OECD 2021). The primary focus of Vietnam's economy has transitioned steadily over time, centering on agricultural exports in the 1990s and labor-intensive manufacturing products such as apparel in the early 2000s. Today, electronics account for half of the country's export value (ibid.). Vietnam's transition into

value-added production has leveraged its relatively advanced education sector. This has generated opportunities for MSMEs, with entry rates of around 100,000 enterprises annually in recent years.[6]

In Vietnam, these structural changes have been paralleled by government efforts to promote SMEs, though these have seen mixed success. Vietnam's initial entrepreneurship and SME policies date back to 2001, when a law was created that defined SMEs,[7] and established an SME development agency. In 2017, a new SME Law was introduced, which covered topics such as taxation, innovation, value chain development, and access to finance. In terms of finance, the Law aimed to facilitate easier access to finance for SMEs by incentivizing banks to allocate at least 30% of their loans to SMEs, with additional tax incentives for startups. Additionally, provincial credit guarantee funds were established, though their effectiveness varies across regions. Private sector initiatives, such as tech startup funds and sector-specific support schemes, have also contributed, particularly for SMEs in emerging sectors like technology and innovation. However, Vietnam still has a significant informal sector, and thus far efforts to formalize informal enterprises have seen mixed success (OECD 2021).

Despite such progress, a significant credit gap persists, especially for women-owned SMEs. According to the General Statistics Office of Vietnam (Viet Nam 2015), MSMEs account for over 98% of all businesses in Vietnam and contribute around 40% of the country's gross domestic product (GDP). However, access to finance remains a significant challenge, particularly for smaller firms. Women-owned SMEs, which represent about 21% of all formal enterprises, are often underserved by banks. These businesses frequently receive less funding and face higher rejection rates for loans, often because of insufficient collateral or perceptions of higher risk.

There has been greater attention to women's SME development since the late 2010s. This has started with efforts by banks to clearly measure lending to women entrepreneurs and then to participate in programs to enhance credit access and human capital of women entrepreneurs.

2.2 Intervention Design

We have partnered with a leading Vietnamese commercial bank to test incentives to increase WSME lending, which were agreed with management in the bank's SME Division to have two main characteristics. First, we agreed on a main outcome of interest: maximizing the *number* of new borrowing WSME customers.[8] Second, we agreed to compare the relative effects of a straightforward piece-rate incentive against a more competitive performance pay system, which

[6] Premia TNC. "Vietnam SME: The Road to Business Success." 4 October 2023. https://premiatnc.com/vn/blog/vietnam-sme/.

[7] Vietnam's SME definitions were updated in the 2018 SME Law, and include definitions based on employees, capital, and revenue. In terms of employees, enterprises with up to 10 employees are considered micro, those with 11–100 (agriculture, forestry, fishery, industry, and construction) or 11–50 (trade and services) are considered small, and those with 101–200 (agriculture, forestry, fishery, industry, and construction) or 51–100 (trade and services) are considered medium.

[8] This paper reports on the results of the phase of this intervention implemented from February to July 2024. There was an earlier attempt to conduct the same experiment in July–December 2023, which faced implementation challenges that prevented effective execution of the intervention. These challenges were addressed in the reported phase.

we call the “contest.” As a result, we designed our study to include two treatment groups and a control group.

The bank, and specifically the SME Division, had prior experience with performance pay incentives. About 50% of lending agents’ pay is based on fixed salary, about 25% is based on performance pay according to Key Performance Indicators (KPIs) focusing on overall portfolio size and quality, and about 25% is based on various incentive programs, which included our program. The other incentive programs typically employ piece-rate rewards for products sold. This could include loans, but also other products such as business accounts, payroll products, business credit cards, trade credit products, and so on. The typical piece rate in these other programs is D500,000 (approximately $20). There were no other incentive programs that specifically targeted women entrepreneurs for regular lending, around and during the time of this study.

2.2.1 Lending Agent Incentives

Incentives within each of the two main treatments were calibrated to result in approximately the same budgets for each of the two treatment arms. Ensuring exactly the same budget was not possible, given that the budget for Treatment 1 was fixed by design whereas the budget for Treatment 2 was dependent on the actual number of WSME loans secured in treated branches.

Treatment 1: The Multi-Category Contest. The contest was designed to optimize competition between lending agents in seeking new WSME clients. It was motivated by the observation that complex tasks with uncertainty in outcomes are often compensated through performance pay mechanisms. At the same time, the contest was designed to be inclusive, in that it offered a schedule of awards, and included subcategories for newer lending agents (“rookies”), and more experienced lending agents who had little prior lending. This inclusive approach was designed to mitigate uneven distribution of effort in winner-take-all contests. At the same time, it offered a convex award schedule, offering outsize rewards to the top performers. Lending agents competed with a large group of agents from other branches in their branch’s group, not just agents within their branch, to mitigate the potential for social tension or collusion.

Hence, the contest has three main categories, which we describe in more detail below. The *ex ante* design of the contest is summarized in Table 1, which is based on available awards, and staff numbers estimated as of December, 2023. In practice, the actual monthly staff numbers could evolve during the intervention phase from February, 2024 to July, 2024. We report relative to averages of the monthly staff numbers over the intervention period.

- **Top WSME lending agents:** This award is for the agents who brought in the most new and inactive (no active loan balance in past 6 months) WSME borrowers in a group, in a focal month. All post-probation lending agents were eligible.

  - *Group 1*: There were 10 potential awards each month across treated urban branches, which was designed with 9% odds of winning. In practice, on average, there were 110 eligible lending agents, leading to average monthly odds of 9%. Average award value was about $82 and increased with rank (Table A1).
  - *Group 2*: There were 5 potential awards each month across treated rural branches, which was designed with 7% odds of winning. In practice, on average, there were 91 eligible lending agents, leading to average monthly odds of 6%. There was an average award value of about $104 that also increased with rank.

- **Most improved WSME lending agents:** This award is also for the agents who brought in the most new and inactive WSME borrowers, but limited to the pool of agents with at least 366 days of continuous tenure at Vietnam Prosperity Bank as of the first day of the month, and a low volume of WSME lending over the previous year (maximum of 2 WSME loans in the past 12 months).
  - *Group 1*: There were 5 potential awards per month, which was designed for a success rate of 10%. However, in practice, only 8 lending agents were eligible on average, leading to a 60% expected success rate.[9] The average award amount was about $72 and increased with rank.
  - *Group 2*: There were 3 potential awards per month, with a designed success rate of 11%. In practice, there were on average 16 eligible lending agents per month, leading to an expected success rate of 19%. The average award amount was about $80.

- **Best new WSME lending agents:** This award for most new WSME borrowers is limited to agents who have 365 days or less of continuous tenure at Vietnam Prosperity Bank as of the first day of the month and have passed the typical 2-month probation period.
  - *Group 1*: There were 5 potential awards each month in this category, with a designed success rate of 12%. In practice, on average there were 54 eligible rookies per month, leading to a 9.3% monthly expected success rate. The average award amount was about $72.
  - *Group 2*: There were 3 potential awards per month, with a designed success rate of 8%. In practice, there were on average 45 eligible lending agents per month, leading to an expected success rate of 6.7%. The average award amount was about $80.

Candidates were eligible to win all awards for which they qualified. For instance, a high-performing lending agent with less than 365 days of tenure could win an award in both the "Top winners" category and the "Best new WSME lender" category. This means that the probability of winning was additive for staff in the second two categories.

[9] The high potential success rate in this category owes largely to substantial departures of qualifying agents in this category from the bank prior to the start of the study. Despite the high potential success rate, few awards were actually given in this category, as most eligible staff had exited the partner bank.

Table 1: Awards Available and Expected Odds of Winning by Group

Number of Awards Available			Expected Odds of Winning		
Top Winners	**Most Improved Lenders**	**Best New WSME Lenders**	**Top Winners**	**Most Improved Lenders**	**Best New WSME Lenders**
Group 1 (4 branches)					
10	5	5	0.09	0.10	0.12
Group 2 (12 branches)					
5	3	3	0.07	0.11	0.08

Source: Authors.

Furthermore, all categories are only applicable to staff who had at least one WSME loan to a new client in the month, so the award numbers are potential, as an award could go unrewarded if there are no qualifying agents. At the same time, ties could lead to more agents receiving an award than planned, if enough agents qualify for the last award slot in a given category. We report on realized awards in Section 3.2.4.

The contest was conducted among lending agents across all branches *within* each group (i.e., within Group 1 or within Group 2). This "pooled, inclusive contest" approach has several advantages:

1. It makes all the contest categories feasible. For instance, some individual provincial branches may not have new lending agents, so the "Best new WSME lender" category would not be meaningful if it were restricted to the branch level.

2. It reduces social tensions within branches, as there are no explicit within-branch contests (though branch staff still compete with each other because they are all part of the same group).

3. It reduces the chances of collusion between lending agents, which has been shown to reduce the effectiveness of relative incentives (e.g., Bandiera, Barankay, and Rasul 2005).

The multi-category contest design was meant to reduce the discouragement effects from winner-take-all designs with heterogeneous participants (Baye, Kovenock, and Vries 1993; Baik 1994; Gradstein 1995). We employ a convex award schedule within each award category, with relatively smaller gaps between award amounts as we go down the table of awards, which has been shown to be theoretically optimal (Lazear and Rosen 1981; Moldovanu and Sela 2001). The full monthly award schedule is presented in Table A1 in the Appendix. Ties in performance lead to prize crowd-out; for example, if two agents tie for first place, then they receive the first-place award, but then there is no second-place award.

We also introduced a random draw incentive, whereby in each of the four (treatment x group) combinations there is an end-of-phase lottery to draw an iPhone. The odds for each lending agent in

this draw were directly proportional to the number of WSME loans they had issued in the quarter—that is, calculated as the proportion of WSME loans they had issued in their (treatment x group) cohort. For example, if Group 1/Treatment 1 has 150 new WSME loans, and Agent A sells 1 loan, (s)he has 1/150 odds for the iPhone, while Agent B with 6 loans has 6/150 odds.

Treatment 2: The Piece Rate. Lending agents received a fixed piece rate of D2 million (approximately $80) for each WSME loan they issued. This is about four times as generous as the typical piece rate offered in other lending agent incentive programs run by the partner bank's SME Division.

2.2.2 Branch and Manager Incentives

The focus of our interventions is on testing variation in pecuniary incentives at lending agent level. Designing these same manager-level incentives into both treatments is meant to keep the focus of comparison between the treatments on the differing levels of *inter-agent competition* in our two treatments. However, to ensure cooperation and participation from branch-level staff and branch managers, and incentivize alignment at all levels, we also include identical contest incentives in *both* treatment arms that were awarded to branches and branch managers. This is intended to align incentives between agents and their managers and thereby make it more likely that managers will clearly communicate the incentive scheme to their agents and support the scheme with the agents under their supervision.

The between-branch contest incentives consisted of top lending awards at the branch level, awarded on a quarterly basis. For Group 1 (urban) branches, there were 3 branch-level awards each quarter, with values ranging from approximately $200 up to $600, depending on a branch's level of performance in the quarter. This means the chances of winning were 3/8 (37.5% could be awarded) per quarter in Group 1 branches. In Group 2 branches, there were 7 awards, with values ranging from $80 to $320, so that 7/24 = 29.2% could receive an award per quarter. These awards are summarized in Appendix Table A3. These branch-level awards were announced to all staff in treatment branches.

The contest incentives also consisted of top lending awards at the branch manager level, which were awarded on a quarterly basis (e.g., two times in each group during the studied intervention, for a total of four awards). The amount of the reward is $200 each time. The chances of winning are proportional to the number of branches in a group, in each quarter—that is, 1/8 in Group 1 (12.5%) and 1/24 (4.2%) in Group 2. These awards are summarized in Appendix Table A4. The branch manager incentives were provided secretly (private announcement only).

2.2.3 Defining Our Study's Main Outcome of Interest

A qualifying credit product application needed to be the first credit product for a new WSME client with the partner bank in one of the following categories:

- Normal term loans, including both collateralized loans and uncollateralized loans;
- Overdraft credit facilities that allow clients to take out more from their bank accounts than they have, up to an agreed-upon limit.

This excludes certain SME credit products such as business credit cards or trade credit.

The new WSME client also had to fit the following specific characteristics:

- Be categorized as what the partner bank terms a “Micro” borrower, which means having annual revenue below about $2.5 million;
- Qualify as what the bank categorizes as a “woman enterprise” (WE), which means the enterprise is woman-owned (at least 50%) or woman-led (at least 50% of company directors are women).

Agents were credited for WSME loans in the month in which the loan application was submitted. For a loan to contribute to the final count for the agent (and their branch) in a particular month, loan approval had to be secured by the 14th day of the month following the application month. If approval occurred on the 15th or later of the subsequent month, the loan was assigned to the loan count for that month after the original focal month. Actual loan disbursement might not occur until subsequent months, but this does not affect the month to which the loan was assigned. Awards were finalized by the end of the month following each focal month.

2.2.4 Overall Award Amounts

The realized amounts of awards were relatively balanced between the two treatment arms, in spite of the fact that the piece-rate allocation was particularly dependent on actual lending. Overall, a total of $18,740 was spent for the contest, and $20,680 was spent on the piece-rate treatment arm.

2.2.5 Scoring Adjustment for Contest Intervention to Account for Variation in Supply of WSMEs Between Provinces

Scoring rules varied slightly between the two branch groups based on the assumption that lending opportunities were relatively more balanced across branches within branch Group 1 than within branch Group 2.

In Group 1, loans were weighted uniformly between branches (e.g., 1 loan in branch A counted the same as 1 loan in branch B, for award purposes). In Group 1 the branches are located in high-density urban areas and economic zones, so we assumed that there is a steady supply of WSMEs across all locations.

However, in Group 2, for both monthly individual awards and quarterly branch and manager awards, the total number of successful loan applications by new WSME clients were adjusted based on a provincial WSME supply index. The provincial WSME supply index was calculated as the ratio of the province’s proportion of women-owned enterprises to the province with the highest

proportion of women-owned enterprises, based on the 2020 Vietnam Enterprise Census. This correction aimed to account for the significant variation in the supply of WSMEs across provinces, which can range from 12% to 38%. This was intended to level the playing field, by giving more credit to Group 2 lending agents who sold a WSME loan in a province with a relatively low proportion of WSMEs, compared to a Group 2 lending agents in a province with a relatively high proportion of WSMEs.

2.2.6 Communication

Communication about each intervention was designed to be as equal as possible across the two treatment arms, so that differences in outcomes between treatments cannot be attributed to differential information sets of the agents. The bank provided information about the interventions in advance of each phase. Then, every 2 weeks, the bank provided email updates to all staff (lending agents and managers) on the progress of WSME lending performance at the branch level, along with a "leaderboard" for the top performers at the lending agent level within each group. Namely, staff at Group 1 branches only see results from Group 1, and staff at Group 2 branches only see results from Group 2.

This communication approach, particularly the mid-month update on progress within the month, should reduce uncertainty about performance, which should improve the effectiveness of the interventions (Lazear and Rosen 1981; Delfgaauw et al. 2014). Staff could also update their beliefs about their relative performance through learning about the actual award winners in the end-of-month updates.

2.3 Hypotheses

Our main hypotheses are as follows:

- **Hypothesis 1a:** The multi-category contest intervention will cause an increase in the number of new WSME borrowers, at both the branch and the lending agent levels.
- **Hypothesis 1b:** The piece-rate intervention will cause an increase in the number of new WSME borrowers, at both the branch and the lending agent levels.
- **Hypothesis 1c:** Female lending agents will respond equally to the incentives as male agents.

We are not hypothesizing which intervention will be more effective relative to the other, as the past literature and other evidence provide mixed guidance. Ultimately, the key competing factor will be how much benefit comes from the greater zero-sum competition in the contest approach. Similarly, the literature offers mixed evidence for setting expectations for whether female or male agents should respond more.

- **Hypothesis 2:** Either incentive, if effective in increasing WSME new borrower loan counts, will cause an increase in aggregate WSME lending volumes and associated bank revenues but a decrease in the average size of WSME loans.

We expect the overall effect on aggregate WSME lending volumes to be positive as an extension of the increased number of WSME loans. However, average WSME loan sizes are likely to decrease because the incentives are based on the number of new WSME clients, rather than loan volumes, and so our incentives should induce smaller loan sizes if smaller loans are easier to sell. Nevertheless, given that other lending agent incentives are still in place to encourage loan size, this effect should be relatively muted.

- **Hypothesis 3:** Either incentive, if effective in increasing WSME new borrower loan counts, will cause an increase in the overall number of new SME borrowers, at both the branch and the lending agent levels——but also a minor reduction in business in non-incentivized product lines.

If Hypothesis 1 holds, then lending agents should be allocating more attention to WSME lending, which may decrease sales in other non-WSME product lines. However, if WSMEs are provided with an inefficiently low amount of financing in the counterfactual, then the incentive program should lead to an improvement in overall lending performance.

3 RESEARCH DESIGN

In this section, we describe our research design. First, we describe the experimental design. Then we report on the actual allocation of treatment, through balance checks. Finally, we describe our econometric frameworks for analyzing treatment effects at the agent level.

3.1 Experimental Design

Our study is conducted in the 50 branches of the bank that conduct Micro (as defined by the partner bank) WSME lending. Ten of these branches (five each in the major urban centers of Hanoi and Ho Chi Minh City) focus exclusively on Micro SME lending. These branches tend to be larger, with a larger number of sales agents divided into a small number of teams, under team managers and an overall branch manager. The other 40 branches, sometimes called “provincial,” target both Micro and “Upper” SME clients (though our incentives are always exclusively targeted at Micro SME clients in both sets of branches).

We allocate the branches into two groups. Group 1 includes the 10 specialized Micro SME branches, along with 3 high-performing provincial branches. Group 2 includes the remaining 37 provincial branches. We implement the interventions and stratify treatment *within* these groups.

We present summary statistics on lending in the 12 months prior to the pilot intervention, in Table 2. The average lending agent in Group 1 sells 0.19 Micro WSME loans per month, whereas

the average Group 2 lending agent sells 0.13 per month. Average monthly lending volumes are $8,484 and $9,221, respectively. We can also observe that lending to non-WSMEs in the Micro category is about three to five times as large.

Table 2: Agents' Average Lending Performance in 12 Months Prior to Intervention Period, by Group

Variable	Group 1 (Urban)			Group 2 (Provincial)		
	No.	Mean	SE	No.	Mean	SE
Number of new Micro WE loans (/month)	2,916	0.19	0.01	1,959	0.13	0.01
Number of new Micro non-WE loans (/month)	2,916	0.88	0.05	1,959	0.52	0.03
Number of new non-Micro WE loans (/month)	2,916	0.01	0.00	1,959	0.04	0.01
Volume of new Micro WE lending ($/month)	2,916	8,484	753	1,959	9,221	762
Volume of new Micro non-WE lending ($/month)	2,916	37,358	2,477	1,959	33,221	1,864
Volume of new non-Micro WE lending ($/month)	2,916	1,110	403	1,959	8,270	1,289

SE = standard error, WE = woman enterprise.
Exchange rate: $1 = D25,000.
Note: Agent-level performance from July 2022 to June 2023, before the pilot intervention phase, represents the number of agent-month observations, i.e., it is the sum of the number of active agents in each of the 12 months. During this period, in Group 1, the monthly minimum number of agents is 198 (July, 2022) and the monthly maximum number of agents is 265 (June, 2023). In Group 2, the equivalent numbers are 127 (July, 2022) and 190 (June, 2023).
Source: Authors' calculations.

Within each group, branches are divided approximately into thirds, for the two treatment arms (piece rate and multi-category contest), and the control.[10] The interventions ran for 6 1-month segments from February to July 2024. Namely, the contest intervention "reset" at the end of each month, with each agent's count returning to zero at the start of the next contest month. Meanwhile, piece rates are awarded on a continual basis.

3.1.1 Randomization

A matched pair randomized design was used. This design first stratified branches by group. For the pilot, within each group, the branches were sorted in order based on administrative data on the number of WSME loans over the 12-month period from April 2022 to March 2023. In Group 1, branches were put in triplets of ascending rank (e.g., those ranked 1–3, 4–6, etc.). Within each triplet, branches were randomly assigned to each of the three arms (Control, Treatment 1, or Treatment 2). In Group 2, the branches were grouped in sets of nine based on the order of ranking of numbers of WSME loans (e.g., those ranked 1–9, 10–18, etc.). Within each set of nine, three branches were randomly assigned to each of the three arms. Branches were then re-randomized for the phase considered in this study. Re-randomization was conditional on the prior allocation; i.e., each branch was allocated to a new treatment arm.

[10] This RCT was cross-randomized with an RCT testing a different set of interventions, which ran partly in parallel. In what follows, we report on the randomization with respect only to the current RCT, not the full cross-randomized design. Where relevant, we control for the presence of any other randomized treatment interventions.

We present balance checks in Appendix Table A5. Balance checks allow us to verify that the randomization was successful in producing statistically balanced treatment and control groups, so that differences between them represent real treatment effects rather than differences in group selection. To do so, we compare agent-level averages of variables between the two treatment arms and control (the first and second column, for T1 and T2, respectively, in consecutive rows) and between T1 and T2 (the third and fourth column), across 12 months from July, 2022, to June, 2023, through t-tests. We report on the p-value of the t-tests; if p-val. > 0.05 then we fail to reject the null hypothesis that the two groups being compared are statistically balanced. We focus on lending outcomes including the number of loans in a number of categories, then separated by gender (including the number of new micro-loans to women SMEs, our target intervention outcome), and the number of female lending agents. While the selected variables provide good coverage of lending outcomes and gendered staffing levels, they do not address secondary business outcomes like differences in lending volumes or other product sales, and they do not address potential differences in baseline attitudes or behaviors of lending agents or branch managers, among others. However, they are still reasonably comprehensive and confirming balance across this set of variables provides reassurance that the randomization was successful.

Table A5 shows there is no evidence of imbalance between the two treatment arms, or between the two treatment arms and the control, based on the selected balancing variables. Nearly all p-values are above 0.2 and many are above 0.5, indicating strong balance in all comparisons. This confirms that the randomization was successful, so the treatment effect analysis can provide insights on the true effect of the interventions.

3.2 Sample and Summary Statistics

3.2.1 Sample

Our study focuses on agents who have passed the bank's initial 2-month probation period for new agents and who have SME lending activity. Hence all summary statistics are based on eligible agents. In any given month, approximately 550 eligible lending agents and their managers are divided across the 50 branches. The urban branches tend to have much larger staff allocations, with about 22 lending agents per branch on average, while provincial branches are typically much smaller, with about 6 staff on average. So, although Group 1 only has 13 branches, it actually has a larger staff allocation, about 60% of the lending agents. Through the randomization design, we exclude about a third of agents in the control group. So, overall, about 370 staff directly participated in the interventions in any month during the study period.

3.2.2 Lending Agents and Managers

Summary statistics on lending agents are presented in Table 3. A majority (57%) of agents are women. The average number of years worked at the bank is just over 2 years, though there is significant dispersion. Notably, the minimum experience is 2.1 months, consistent with our

censoring agents still on 2-month probation, who are ineligible for our study incentives. The average lending agent is 28 years old.

Table 3: Summary Statistics for Lending Agents

Variable	Obs	Mean	SD	Min.	Max.
Gender (female = 1)	554	0.57	0.50	0	1
Tenure (months)	554	24.91	25.68	2	215
Age	553	27.96	5.00	21	64

Max. = maximum, Min. = minimum, Obs = observations, SD = standard deviation.
Note: Agent-level characteristics as of June 2023, before the pilot intervention phase.
Source: Authors' calculations.

There are 87 managers divided across the branches. Typically, the provincial branches have a single branch manager, while the urban branches tend to have multiple teams of sales staff with team managers, supervised by a branch manager.

Summary statistics on managers are presented in Table 4. In contrast to agents, only 18% of managers are women. The average tenure at the bank is about 7 years. The average manager is 37 years old.

Table 4: Summary Statistics for Managers

Variable	Obs	Mean	SD	Min.	Max.
Gender (female = 1)	87	0.18	0.39	0	1
Tenure (months)	87	83.42	65.11	4	232
Age	87	36.87	4.72	29	50

Max. = maximum, Min. = minimum, Obs = observations, SD = standard deviation.
Note: Manager-level characteristics as of June 2023, before the pilot intervention phase.
Source: Authors' calculations.

3.2.3 Loans

We present summary statistics on loans *during* the intervention period in Table 5, broken down by group. This includes loans in both treatment arms and the control. Overall, we observe the allocation of $34 million in approved loan amounts for 584 loans. We observe 376 loans for $19 million in Group 1, and 208 loans for $15 million in Group 2. The average approved loan size is $50,337 in the urban branches and $72,906 in the provincial branches. The average loan contract term (tenure) is 2–2.5 years, with a longer average loan length in urban areas. Average interest rates are in the 11% range, slightly higher in provincial branches, but in line with SME lending rates at the time. Non-delinquency, defined as not having had a loan payment at least 10 days overdue, approaches 98% across both groups. A total of 50%–60% of loans are in normal, secured lending, with a large minority share in unsecured lending and 5%–10% in overdrafts.

Table 5: Characteristics of Loans During Intervention Period, by Group

	Group 1 (Urban)	Group 2 (Provincial)
Number of loans	376	208
Total approved amount ($)	18,926,615	15,164,435
Average loan size, approved amount ($)	50,337	72,906
	(92,932)	(191,527)
Average loan terms (months)	29.42	22.44
	(27.70)	(25.44)
Average interest rate (%)	10.75	11.79
	(3.29)	(3.91)
Share of loans without delinquency (%)	97.70	97.70
Share of overdrafts (%)	4.79	9.13
Share of normal lending—secured (%)	60.91	49.52
Share of normal lending—unsecured (%)	34.30	41.35

Exchange rate: $1 = D25,000.
Notes: Characteristics of 584 loans, from both treatment and control branches. Standard deviation is in parentheses.
Source: Authors' calculations.

The distribution of loans is broken down by sector in each group in Table 6. Across numerous markets, WSMEs tend to cluster in certain sectors such as retail, food and beverages, hospitality, and fashion. On the other hand, lending may be attracted to more capital-intensive sectors, or sectors where banks have more familiarity.

We observe that the largest proportions of loans are in the wholesale and retail sectors, with 43% and 51%, respectively. However, in the urban branches, this is followed by transport and logistics, and manufacturing. In the provincial branches, manufacturing is second-ranked, followed by construction. Hence it is notable that some of the most important lending sectors remain similar across the two groups of branches.

Table 6: Distribution of Loans by Sector, by Group

Group 1: Urban Branches			Group 2: Provincial Branches		
Industry	**Freq.**	**%**	**Industry**	**Freq.**	**%**
Wholesale and retail; motorbike, automobile, and engine repairing services	161	42.82	Wholesale and retail; motorbike, automobile, and engine repairing services	106	51.21
Transportation and logistics	62	16.49	Manufacturing	36	17.39
Manufacturing	50	13.30	Construction	19	9.18
Others	103	27.39	Services and hospitality	12	5.77
			Others	35	16.83

Freq. = frequency.
Notes: Distribution of loan sectors across 584 loans from both treatment and Control branches in Group 1 (376 loans) and Group 2 (208 loans).
Percentages denote share of total loans within each group.
Source: Authors' calculations.

3.2.4 Realized Awards

We reported the awards available *ex ante* in Section 2.2.1. However, in practice, fewer or more awards could be provided than available. Fewer could be provided if there were not enough eligible winners (e.g., not enough lending agents, in a sub-category, with at least one qualifying loan). More could be provided than planned if there were ties for the last award slot.[11]

We report on the available awards against the realized awards in Table A2. Here we can observe that the expected awards to "Top Winners" and "Best New WSME Lenders" were generally awarded. Significantly fewer tended to be awarded in the first month (February, 2024), but in subsequent months there were almost always as many prizes awarded as available. Indeed, in Group 2, two extra "Top Winners" prizes were awarded in months 2-6, and one extra prize was awarded in two different months in Group 1. However, it is also notable that fewer "Most Improved Lenders" awards were realized than planned. Most striking is that there were 0 awards across all months for this category in Group 2. In Group 1 there were also fewer awards than available, and in month 3 all 5 prizes were awarded.

3.2.5 Data and Temporal Variation

The analysis utilizes administrative data, including outcomes that were aggregated monthly throughout the study period. Administrative data were collected beginning April 2022 through the end of 2025 from internal records maintained by the partner bank, and relevant subsets of temporal coverage are used for the analysis. In particular, some descriptive analyses such as summary statistics and balance checks include pre-intervention data (prior to pilot phase) from mid-2022 to mid-2023. All of the main regression tables are based on 18 months of data, 12 pre-treatment (February, 2023 to January, 2024) and 6 during-treatment (February, 2024 to July, 2024). We also report on some post-treatment outcomes measured in 2025, e.g., for loan delinquency analysis.

3.2.6 Sample Selection

In practice, some branch-level sales agents are not involved in lending. Particularly in urban branches, some agents are assigned to roles that are focused on cultivating existing clients rather than seeking out new ones. As these agents are essentially ineligible for the incentives that we are testing, we exclude from our analysis all agents who *never* issue an SME loan (male or female) during our study period of 18+ months. This selection criterion reduces the number of lending agents by about 30%.

Our sample is focused on outcomes for our eligible lending categories—new and inactive borrowers. We exclude the category of existing, active borrowers from consideration, as their loans were not eligible for incentive rewards to loan agents.

[11] In practice, our budget was flexible enough to allow a slightly larger number of awards, where necessary.

3.3 Empirical Methodology

Agent-level treatment effects are estimated using standard linear panel models with ordinary least squares. We begin by estimating a pooled treatment specification that captures the average effect of being exposed to any incentive intervention, irrespective of treatment type. We then extend the analysis to estimate disaggregated treatment effects that separately identify the impacts of the contest and piece-rate treatments. Finally, we present heterogeneity analysis.

3.3.1 Pooled Treatment Effects Specification

The pooled treatment model provides an overall estimate of the average effect of exposure to any treatment.

Specifically, we estimate:

$$Y_{ibt} = \beta D_{\text{Treatment},b,t} + \gamma' X_{ibt} + \alpha_i + \lambda_t + \varepsilon_{ibt}, \tag{1}$$

where:

- i indexes individual lending agents,
- b indexes bank branches,
- t indexes month time periods,
- Y_{ibt} denotes the outcome of interest for agent i in branch b at time t,
- $D_{\text{Treatment},b,t}$ is a dummy equal to 1 if branch b is assigned to any treatment (contest or piece rate) at time t, and 0 otherwise,
- X_{ibt} is a vector of time-varying controls, which consist of dummies for lagged branch treatment in the t-7 pilot period in all specifications and add the interaction of the lagged treatment with whether the branch is urban or agent is female in corresponding heterogeneous treatment effect runs described in Equation 3,
- α_i are agent fixed effects,
- λ_t are time fixed effects, and
- ε_{ibt} is the idiosyncratic error term, clustered at the branch level to account for correlation in unobserved shocks within branches over time.

The coefficient β captures the pooled average treatment effect of participating in any incentive intervention, relative to control branches. This specification provides a parsimonious summary measure of the overall treatment impact before disaggregating by specific treatment arm.

3.3.2 Disaggregated Treatment Effects Specification

We next distinguish between the two treatment types—contest and piece rate—by estimating separate coefficients for each. The model is specified as:

$$Y_{ibt} = \beta_1 D_{\text{Contest},b,t} + \beta_2 D_{\text{PieceRate},b,t} + \gamma' X_{ibt} + \alpha_i + \lambda_t + \varepsilon_{ibt}, \tag{2}$$

where the variables are defined as above. The coefficients β_1 and β_2 identify the average treatment effects of the contest and piece-rate interventions, respectively.

3.3.3 Heterogeneous Treatment Effects

To explore heterogeneity in treatment impacts, we extend our analysis by interacting the treatment indicators with key agent- and branch-level characteristics. Specifically, we examine whether the treatment effects differ between (i) agents working in *rural* versus *urban* branches and (ii) *male* versus *female* loan agents. The heterogeneous effects are estimated using the following specification:

$$Y_{ibt} = \beta_1 D_{\text{Treatment},b,t} + \beta_2 D_{\text{Treatment},b,t} \times Z_{ib} + \gamma' X_{ibt} + \alpha_i + \lambda_t + \varepsilon_{ibt}, \tag{3}$$

where Z_{ib} is an indicator for the relevant subgroup characteristic, such as being located in a rural branch or being a female loan agent. The interaction term captures how the treatment effect varies with the characteristic of interest.

We estimate this model both for the pooled treatment indicator and for disaggregated treatments (contest and piece rate) separately. After estimation, we use the `lincom` command in Stata to compute the linear combination of coefficients corresponding to the subgroup-specific treatment effects (termed “lincom” in tables), and to obtain the associated standard errors. This allows us to formally test hypotheses such as whether the treatment effect for rural branches differs from that for urban branches, or whether the effect for female agents differs from that for male agents.

The resulting estimates provide insight into the heterogeneity of behavioral responses to incentive interventions, shedding light on how context and agent characteristics shape the effectiveness of performance-based incentives.

4 RESULTS

We present our estimates of the effects of the interventions on our primary outcomes: number and volume of loans. Next, we consider the possibility that our interventions may create trade-offs, through adverse impacts on other outcomes for the bank. We consider (i) a strategic reduction in average loan size by loan agents, (ii) adverse spillovers to other lines of business (loans to males in the same loan size category), and (iii) greater risk-taking by lending agents, through higher

delinquency among new female clients targeted by our incentives. Finally, we study heterogeneous treatment effects by gender of the lending agents.

In each table of the main results, in the first column we present “pooled” treatment effects, combining both treatment arms in one coefficient. In the second column, we disaggregate the pooled effect by rural–urban. In the third column, we disaggregate effects by treatment arms, and finally, in the fourth column, we disaggregate treatment arm effects by rural–urban.

4.1 Main Impacts: WSME Lending

We begin by showing our main results: the impacts of the interventions on lending to new or inactive WSMEs in the partner bank’s Micro lending category.

Table 7 presents the estimated effects of the two incentive interventions on the number of new WSME loans issued per lending agent per month. This was the primary outcome incentivized by the intervention. The mean of the dependent variable in the control group is 0.19, implying that the average agent issues roughly one new WSME loan every 5 months, in the absence of incentives, during our intervention period.

Table 7: Effect of Treatments on Number of New WSME Loans

	(1)	(2)	(3)	(4)
Pooled treatment	0.075*			
	(0.041)			
Pooled treatment (Rural)		0.062		
		(0.038)		
Pooled treatment × Urban		0.025		
		(0.053)		
T1—Contest			0.110*	
			(0.057)	
T2—Piece rate			0.053	
			(0.043)	
T1—Contest (Rural)				0.066*
				(0.033)
T1—Contest × Urban				0.086
				(0.085)
T2—Piece rate (Rural)				0.061
				(0.050)
T2—Piece rate × Urban				-0.016
				(0.063)
Lincom est. T + (T × Urban)		0.087		
Lincom SE T + (T × Urban)		(0.056)		
Lincom est. T1 + (T1 × Urban)				0.152*
Lincom SE T1 + (T1 × Urban)				(0.089)
Lincom est. T2 + (T2 × Urban)				0.045
Lincom SE T2 + (T2 × Urban)				(0.056)
N.	10,010	10,010	10,010	10,010
R^2	0.157	0.157	0.157	0.157
Control variables	Lagged treatment	Lagged treatment	Lagged treatment	Lagged treatment
FE	Month-by-year, Staff ID	Month-by-year, Staff ID	Month-by-year, Staff ID	Month-by-year, Staff ID
Cluster	Branch ID	Branch ID	Branch ID	Branch ID
Model	OLS	OLS	OLS	OLS
Mean control group	0.190	0.190	0.190	0.190

est. = estimated, FE = fixed effects, ID = identifier, N. = number, OLS = ordinary least squares, SE = standard error, T = Treatment, T1 = Treatment 1, T2 = Treatment 2.
Note: Model includes month-by-year and staff ID fixed effects and branch ID clustering. In heterogeneous effects specifications “Lagged treatment” also includes interaction of lagged treatment with Urban. Robust standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01.
Source: Authors’ calculations.

In the pooled specification, which aggregates the two treatments, exposure to any incentive program raises the number of new WSME loans by 0.075 per agent-month, or close to 40% relative to the control mean, significant at 10%. This average effect masks important heterogeneity across branch types. When we disaggregate by branch, the pooled treatment effect is positive in both rural and urban branches but notably larger in urban areas,[12] consistent with the view that incentive pay may be particularly effective in markets where baseline effort or opportunity is lower.

[12]The coefficients labeled as (x Rural) are the base rate in rural (aka provincial) branches, while those labeled (x Urban) are the additional marginal effects in urban branches.

Column (3) distinguishes between the contest (T1) and piece-rate (T2) treatments. Both increase WSME loan acquisition, but the contest produces about double the magnitude of gain, which is significant at 10%. Agents in contest branches issue about one-tenth of a loan more per month than those in control branches, a 58% increase.

The final column explores heterogeneous treatment effects by branch type. The interaction terms and linear combinations show that the has substantially higher coefficients in urban areas, while the piece rate performs marginally better than the contest in rural areas. In rural areas, the contest increases monthly WSME lending by 0.07 loans per agent—almost a one-third increase relative to the control mean—while the piece rate yields an increase of about 0.06. In urban branches the effect is further boosted to around 0.15 for the contest, while it is slightly mitigated for the piece rate. These results suggest that contest incentives are especially effective where there is more economic activity.

Taken together, the findings in Table 7 indicate that financial incentives for WSME recruitment substantially raise new client acquisition on average, with stronger effects in urban markets and some evidence that the contest format modestly outperforms the simpler piece rate.

Next, we show the impact of the treatments on the volume of WSME loans in Table 8. It is notable that volume was not explicitly incentivized by the program. Our control group mean is $9,750 per loan agent per month.

Table 8: Effect of Treatments on Volume of New WSME Loans ($)

	(1)	(2)	(3)	(4)
Pooled treatment	720			
	(4,586)			
Pooled treatment (Rural)		-2,229		
		(6,077)		
Pooled treatment × Urban		5,505		
		(5,290)		
T1—Contest			-123	
			(5,812)	
T2—Piece rate			1,264	
			(4,823)	
T1—Contest (Rural)				-5,205
				(8,485)
T1—Contest × Urban				9,710
				(8,799)
T2—Piece rate (Rural)				-223
				(6,841)
T2—Piece rate × Urban				2,805
				(5,951)
Lincom est. T + (T × Urban)		3,276		
Lincom SE T + (T × Urban)		(4,378)		
Lincom est. T1 + (T1 × Urban)				4,505
Lincom SE T1 + (T1 × Urban)				(5,476)
Lincom est. T2 + (T2 × Urban)				2,582
Lincom SE T2 + (T2 × Urban)				(4,391)
N.	10,010	10,010	10,010	10,010
R^2	0.081	0.081	0.081	0.081
Control variables	Lagged treatment	Lagged treatment	Lagged treatment	Lagged treatment
FE	Month-by-year, Staff ID	Month-by-year, Staff ID	Month-by-year, Staff ID	Month-by-year, Staff ID
Cluster	Branch ID	Branch ID	Branch ID	Branch ID
Model	OLS	OLS	OLS	OLS
Mean control group	9,750	9,750	9,750	9,750

est. = estimated, FE = fixed effects, ID = identifier, N. = number, OLS = ordinary least squares, SE = standard error, T = Treatment, T1 = Treatment 1, T2 = Treatment 2.
Note: Model includes month-by-year and staff ID fixed effects and branch ID clustering. In heterogeneous effects specifications "Lagged treatment" also includes interaction of lagged treatment with Urban. Robust standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01.
Source: Authors' calculations.

Here, our agent-level effects are much more muted, with smaller point estimates relative to standard errors. When we pool treatment effects, coefficients vary from positive in urban areas to negative in rural areas, which averages to a small average amount, less than 10% of the monthly average per loan agent. When we disaggregate by treatment arm, we see that the pooled treatment effect masks heterogeneity between the piece rate (positive coefficient) and the contest (very small, negative coefficient). When we disaggregate treatment arms by urban versus rural in column (4), we see that the contest has a large negative coefficient in rural areas and a large positive one in

urban areas, nearly equal to the control group average, albeit still insignificant. Piece-rate effects are more muted, and relatively larger again in urban areas.

While we observe significant positive effects of our treatments on our main outcome, number of new WSME clients, particularly in the contest and in urban areas, effects are much more noisy on volume.

4.2 Prospective Spillovers and Trade-offs

In this section, we consider the possibility that, even if our intervention is effective in increasing the number of loans, particularly in urban branches, there may be trade-offs in inducing this effect.

We consider three possibilities. First, that the incentives induce loan agents to pursue smaller average loan sizes. If smaller loans are easier to sell, then loan agents may be incentivized to pursue smaller loan sizes. Second, that the incentives cause adverse spillovers on other parts of the lending portfolio. We focus on lending to new male entrepreneurs in the same loan size category as the women entrepreneurs targeted by our incentives. Finally, we consider that incentivizing lending may induce greater risk taking by loan agents, as our incentives compensate for loss of income from agents' core KPIs, owing to lower portfolio quality.

4.2.1 Average Loan Sizes

We study the effect of treatment on average loan sizes—essentially the ratio of our two previous outcome variables (volume divided by number of loans)—in Table 9. One possibility is that agents will become more likely to optimize on loan seeking by reducing average loan size as the program goes on (as incentives are tied only to number and not to volume of loans). We might particularly expect this later in the intervention period, if agents catch on and become more strategic, and more of their deal flow has been generated during the intervention period.

However, we do not find significant evidence for this hypothesis. We find relatively muted effects on average loan size across the pooled and treatment-disaggregated specifications. In column (4), we see that these average effects mask significant within-treatment heterogeneity by urban–rural, with economically significant positive and negative coefficients. However, standard errors continue to be much larger than point estimates, so we can rule out the hypothesis that the interventions decrease average loan size.

Table 9: Effect of Treatments on Average WSME Loan Size ($)

	(1)	(2)	(3)	(4)
Pooled treatment	193			
	(2,969)			
Pooled treatment (Rural)		270		
		(4,109)		
Pooled treatment × Urban		-140		
		(3,304)		
T1—Contest			-554	
			(3,451)	
T2—Piece rate			674	
			(3,259)	
T1—Contest (Rural)				-1,676
				(5,251)
T1—Contest × Urban				2,268
				(5,118)
T2—Piece rate (Rural)				1,571
				(4,994)
T2—Piece rate × Urban				-1,679
				(4,193)
Lincom est. T + (T × Urban)		130		
Lincom SE T + (T × Urban)		(2,611)		
Lincom est. T1 + (T1 × Urban)				592
Lincom SE T1 + (T1 × Urban)				(3,115)
Lincom est. T2 + (T2 × Urban)				-108
Lincom SE T2 + (T2 × Urban)				(2,532)
N.	10,010	10,010	10,010	10,010
R^2	0.082	0.082	0.082	0.083
Control variables	Lagged treatment	Lagged treatment	Lagged treatment	Lagged treatment
FE	Month-by-year, Staff ID	Month-by-year, Staff ID	Month-by-year, Staff ID	Month-by-year, Staff ID
Cluster	Branch ID	Branch ID	Branch ID	Branch ID
Model	OLS	OLS	OLS	OLS
Mean control group	7,011	7,011	7,011	7,011

est. = estimated, FE = fixed effects, ID = identifier, N. = number, OLS = ordinary least squares, SE = standard error, T = Treatment, T1 = Treatment 1, T2 = Treatment 2.

Note: Model includes month-by-year and staff ID fixed effects and branch ID clustering. In heterogeneous effects specifications "Lagged treatment" also includes interaction of lagged treatment with Urban. Robust standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

Source: Authors' calculations.

4.2.2 Spillovers on Non-WSME Lending

One concern with our interventions is that, if the bank incentivizes lending to WSMEs, then agents will simply shift their efforts toward WSMEs and away from other sales activities, substituting one area of sales for another. In the extreme, our intervention might not have any effect on overall branch-level performance.

To test this, we focus on the most obvious potential area for substitution—non-WSME Micro SME lending. We show the effect of our treatments on the number of new and inactive non-WSME loans in Table 10.

We do not find effects supporting this concern. There are no significant negative point estimates. In fact, the only statistically significant point estimates are positive: our incentive program, which focuses on WSME lending, causes an increase in non-WSME lending in rural areas, and this effect is clearer for the piece-rate intervention. In any case, we can reject the hypothesis that our intervention causes crowd-out in the most obvious product line for negative spillovers.

Table 10: Effect of Treatments on Number of New Non-WSME Loans

	(1)	(2)	(3)	(4)
Pooled treatment	0.122			
	(0.098)			
Pooled treatment (Rural)		0.180*		
		(0.096)		
Pooled treatment × Urban		-0.108		
		(0.095)		
T1—Contest			0.122	
			(0.121)	
T2—Piece rate			0.121	
			(0.103)	
T1—Contest (Rural)				0.168
				(0.112)
T1—Contest × Urban				-0.081
				(0.168)
T2—Piece rate (Rural)				0.188*
				(0.109)
T2—Piece rate × Urban				-0.126
				(0.108)
Lincom est. T + (T × Urban)		0.072		
Lincom SE T + (T × Urban)		(0.119)		
Lincom est. T1 + (T1 × Urban)				0.086
Lincom SE T1 + (T1 × Urban)				(0.170)
Lincom est. T2 + (T2 × Urban)				0.063
Lincom SE T2 + (T2 × Urban)				(0.123)
N.	10,010	10,010	10,010	10,010
R^2	0.211	0.211	0.211	0.211
Control variables	Lagged treatment	Lagged treatment	Lagged treatment	Lagged treatment
FE	Month-by-year, Staff ID	Month-by-year, Staff ID	Month-by-year, Staff ID	Month-by-year, Staff ID
Cluster	Branch ID	Branch ID	Branch ID	Branch ID
Model	OLS	OLS	OLS	OLS
Mean control group	0.730	0.730	0.730	0.730

est. = estimated, FE = fixed effects, ID = identifier, N. = number, OLS = ordinary least squares, SE = standard error, T = Treatment, T1 = Treatment 1, T2 = Treatment 2.
Note: Model includes month-by-year and staff ID fixed effects and branch ID clustering. In heterogeneous effects specifications "Lagged treatment" also includes interaction of lagged treatment with Urban. Robust standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01.
Source: Authors' calculations.

To further corroborate this finding, we show the volume of non-WSME loans in Table 11. Once again, nearly all point estimates are above zero, though none are significant. However, we do observe a very large, negative coefficient under the piece rate in urban areas, though it is not statistically significant.

Table 11: Effect of Treatments on Volume of New Non-WSME Loans ($)

	(1)	(2)	(3)	(4)
Pooled treatment	3,474			
	(9,098)			
Pooled treatment (Rural)		11,851		
		(13,568)		
Pooled treatment × Urban		-15,632		
		(14,267)		
T1—Contest			11,032	
			(9,554)	
T2—Piece rate			-1,399	
			(11,623)	
T1—Contest (Rural)				9,769
				(17,055)
T1—Contest × Urban				2,499
				(17,509)
T2—Piece rate (Rural)				13,769
				(18,828)
T2—Piece rate × Urban				-27,634
				(19,829)
Lincom est. T + (T × Urban)		-3781		
Lincom SE T + (T × Urban)		(8,817)		
Lincom est. T1 + (T1 × Urban)				12,268
Lincom SE T1 + (T1 × Urban)				(7,611)
Lincom est. T2 + (T2 × Urban)				-13,900
Lincom SE T2 + (T2 × Urban)				(10,430)
N.	10,010	10,010	10,010	10,010
R^2	0.103	0.103	0.103	0.103
Control variables	Lagged treatment	Lagged treatment	Lagged treatment	Lagged treatment
FE	Month-by-year, Staff ID	Month-by-year, Staff ID	Month-by-year, Staff ID	Month-by-year, Staff ID
Cluster	Branch ID	Branch ID	Branch ID	Branch ID
Model	OLS	OLS	OLS	OLS
Mean control group	33,869	33,869	33,869	33,869

est. = estimated, FE = fixed effects, ID = identifier, N. = number, OLS = ordinary least squares, SE = standard error, T = Treatment, T1 = Treatment 1, T2 = Treatment 2.
Note: Model includes month-by-year and staff ID fixed effects and branch ID clustering. In heterogeneous effects specifications "Lagged treatment" also includes interaction of lagged treatment with Urban. Robust standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01.
Source: Authors' calculations.

Overall, it appears that our intervention does not cause excessive negative spillovers on non-WSME lending. If anything, there are positive spillovers. However, we acknowledge that this analysis is limited to SME lending and we may not be picking up negative spillovers on other sales activities—-for example on Upper SME lending in provincial branches or on other credit products (e.g., credit cards)—or simply onboarding of new clients to business accounts with our partner bank. We will study these outcomes in future analysis.

4.2.3 Do the Interventions Lead to Lower-Quality Loans?

Another potential concern is that the incentives could induce loan agents to sell lower-quality loans. While this possibility should be mitigated by the multilayered loan approval process in the partner bank, whereby loan agents do not have final say on loan approvals, more risk is still possible on the margin, especially if agents have tacit knowledge that is unobservable to the bank.

We can examine this by looking at non-delinquency rates amongst our 584 study Micro WSME loans as of July 2025, by comparing treatment arms to the control in Table 12. Notably, we use a very weak definition of delinquency: 10 days' payment delinquency.[13] We observe a zero rate of full default in our study portfolio as of July 2025. Note that, since some of the loans are still active (the intervention ended in July 2024), there may still be some potential for delinquency to increase. However, from what we can see in the fourth and fifth columns, which show p-values of a test comparing each treatment group to the control, differences are largely insignificant, though the comparison between contest and control is significant at 10% when pooling all branches. Point estimates for urban branches (which along with urban branches have less statistical power in the t-tests, due to smaller sample sizes disaggregating by group) reveal that the slightly higher delinquency is in the urban locations. In any case, there is limited evidence that the interventions cause significant increases in risk-taking.

Table 12: Effect of Treatments on On-Time Repayment (non-delinquency)

	Contest	Piece Rate	Control	(C. vs Contr.)	(P. vs Contr.)
All branches	0.968	0.988	0.993	0.0592*	0.216
	(0.013)	(0.008)	(0.007)		
Group 1 (Urban)	0.960	0.981	0.989	0.103	0.325
	(0.018)	(0.011)	(0.011)		
Group 2 (Provincial)	0.985	0.989	1.000	0.180	0.214
	(0.015)	(0.011)	(0.000)		

C = Contest, Contr. = Control, P = Piece rate, vs = versus.
Notes: Delinquency is defined as whether the loan has an overdue payment exceeding 10 days. Standard errors are shown in parentheses. Columns 4 and 5 present the p-value of t-tests between Contest vs Control and Piece rate vs Control, respectively. Calculated based on 584 loans in Phase 2. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.
Source: Authors' calculations.

4.3 Heterogeneity of Treatment Effects by Agent Gender

A large literature suggests that women often respond less favorably to competition than men (e.g., Niederle and Vesterlund 2011) and that they may have relatively weaker performance when competing directly with men (e.g., Gneezy, Niederle, and Vesterlund 2003). On the other hand, our setting is a high-stakes, relatively high-skill one, where men and women are selected from a large labor pool, and persist over time. Overall, about 55% of the lending agents are women.

We produce an agent-level result for heterogeneity in treatment effects by gender of the agent, in Tables 13 (number of loans) and 14 (volume). Our findings refute the patterns in the prior

[13] Conventional measures of delinquency for banks tend to be between 90 and 180 days.

literature. We find quite strong evidence that female loan agents *outperform* male loan agents (the linear combination of coefficients estimate is 0.105, nearly a 50% increase relative to the control mean of 0.19, which is significant at 5%). When we disaggregate by treatment arm, we find that the female agents actually particularly *outperform* under the contest, with a very large linear combination coefficient of 0.146 (about 77% of the control mean) under the contest. There are substantial effects for the piece rate, too, but they are not statistically significant.

Table 13: Heterogeneity in the Effects of Treatment by Agent Gender, Number of WSME Loans

	(1)	(2)
Pooled treatment (Male)	0.035	
	(0.035)	
Pooled treatment x Female	0.069*	
	(0.036)	
T1—Contest (Male)		0.055
		(0.039)
T2—Piece rate (Male)		0.024
		(0.042)
T1 x Female		0.090
		(0.062)
T2 x Female		0.052
		(0.040)
Lincom est. T + (T x Female)	0.105 **	
Lincom SE T + (T x Female)	(0.049)	
Lincom est. T1 + (T1 x Female)		0.146 *
Lincom SE T1 + (T1 x Female)		(0.076)
Lincom est. T2 + (T2 x Female)		0.076
Lincom SE T2 + (T2 x Female)		(0.051)
N.	10,010	10,010
R^2	0.157	0.157
Control variables	Lagged treatment	Lagged treatment
FE	Month-by-year, Staff ID	Month-by-year, Staff ID
Cluster	Branch ID	Branch ID
Model	OLS	OLS
Mean control group	0.190	0.190

est. = estimated, FE = fixed effects, ID = identifier, N. = number, OLS = ordinary least squares, SE = standard error, T = Treatment, T1 = Treatment 1, T2 = Treatment 2
Notes: Model includes month-by-year and staff ID fixed effect and branch ID cluster. In heterogeneous effects specifications "Lagged treatment" also includes interaction of lagged treatment with Female. Robust standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01.
Source: Authors' calculations.

The patterns are somewhat different for volume. Effects on volume have less statistical significance, in part due to noise in the data. The piece-rate coefficient on volume for female loan agents is about 73% the value of the control mean, but it is not significant (although the interaction term indicates a significant difference from male agents).

Table 14: Heterogeneity in the Effects of Treatment by Agent Gender, Volume of WSME Loans (USD)

	(1)	(2)
Pooled treatment (Male)	-4,115	
	(5,640)	
Pooled treatment x Female	8,435	
	(5,649)	
T1—Contest (Male)		-382
		(10,227)
T2—Piece rate (Male)		-6,301
		(5,108)
T1 x Female		478
		(9,695)
T2 x Female		13,599**
		(6,285)
Lincom est. T + (T x Female)	4,320	
Lincom SE T + (T x Female)	(5,098)	
Lincom est. T1 + (T1 x Female)		96
Lincom SE T1 + (T1 x Female)		(4,927)
Lincom Est. T2 + (T2 x Female)		7,298
Lincom SE T2 + (T2 x Female)		(6,111)
N.	10,010	10,010
R^2	0.081	0.081
Control variables	Lagged treatment	Lagged treatment
FE	Month-by-year, Staff ID	Month-by-year, Staff ID
Cluster	Branch ID	Branch ID
Model	OLS	OLS
Mean control group	9,750	9,750

est. = estimated, FE = fixed effects, ID = identifier, N. = number, OLS = ordinary least squares, SE = standard error, T = Treatment, T1 = Treatment 1, T2 = Treatment 2
Notes: Model includes month-by-year and staff ID fixed effect and branch ID cluster. In heterogeneous effects specifications "Lagged treatment" also includes interaction of lagged treatment with Female. Robust standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01.
Source: Authors' calculations.

5 CONCLUSION

We conduct an impact evaluation of incentives intended to increase new client lending to women entrepreneurs by a leading commercial bank in Vietnam. Namely, we compare two incentive treatments for loan agents—piece rates and a multi-category contest—to a control. In theory, in our high-stakes, real-world setting, with an uncertain output (SME loans), competitive incentives may be more effective in motivating performance. However, other factors may play a role, such as aversion to competition, risk preferences, and information asymmetries. There is scant experimental evidence from high-stakes field contexts on whether piece rates or contest incentives can better drive performance for similar task contexts, much less in our specific context of bank lending. Our analysis is based on administrative data from the partner bank that implemented the treatments with its own agents.

Our results show that financial incentives for loan agents substantially increased lending to women-owned and -led small and medium-sized enterprises (WSMEs). On average, exposure to any incentive program raised the number of new WSME loans issued per agent-month by roughly 40% relative to the control mean, with larger gains in urban branches, where economic activity and lending potential are greater. This was primarily driven by the contest, which generated about twice the improvement of the piece rate. These results suggest that incentive pay can meaningfully improve inclusion outcomes in commercial banking, especially in markets where loan agents face weaker intrinsic motivation or lower opportunity.

We document that female loan agents respond at least as strongly as, and often more strongly than, their male counterparts-—particularly under the contest scheme for number of loans, and piece rates for volume of loans-—contrary to prior findings that women underperform in competitive settings (Niederle and Vesterlund 2011). However, a more nuanced consideration of the literature suggests there is precedent for this result. Women have been found to respond more competitively than men to competitive tasks that they think conform to female roles, so that they are likely to win (Günther et al. 2010). Female lending agents may view recruiting WSME clients, who are often female, as a role for which they have a competitive advantage over men, and respond more competitively as a result. Nonetheless, this prior work was conducted in a lab setting, while our study corroborates this finding in a high-stakes, field setting.

Finally, we find little evidence of adverse side effects. The increase in loan numbers was not accompanied by reductions in average loan size, declines in loan quality, or crowding-out of other lending activity. On the contrary, there are hints of positive spillovers to lending to male entrepreneurs in the same portfolio. One explanation for this latter result is that the categorization of male- and female-led enterprises on prospective client lists tend to be imperfect, so our incentives may have induced increased male lending as lending agents searched over imperfect prospect lists and also picked up new male clients along the way. Together, the evidence indicates that well-designed incentive pay can enhance financial inclusion without compromising portfolio quality or fairness, and that gender composition and market context shape the effectiveness of incentive mechanisms in important ways.

These results provide important insights on the organizational economics of lending to women entrepreneurs in financial institutions in emerging markets. We find that both treatments are effective in driving a significant increase in the number of new WSME clients, the main objective of our program. The partner bank was particularly interested to target new clients, who have the potential to grow with the bank and drive future volume and revenues. Importantly, there are apparently few significant trade-offs to doing so—we do not observe lending agents strategically decreasing loan sizes, reducing their lending in other areas, or taking on riskier loans. This suggests the baseline level of focus on WSME lending in this market was inefficiently low, with opportunities available for financial institutions to increase both equity and efficiency by targeting underserved WSME clients. This raises questions about what frictions might prevent more optimal allocations of lending agent effort. This question is left for future work.

Looking ahead, our findings point to several design principles for improving WSME-focused incentive programs in commercial banks. The difference in effectiveness suggests that contest incentives may be more effective in driving desired behavioral changes than simple piece rate payments. While the interventions delivered sizable gains in WSME lending without adverse portfolio effects, they did so with relatively generous incentive amounts and only among certain groups of staff, such as female agents. This suggests that better segmentation based on perceived comparative advantage in winning the contest could make the incentives motivate more staff. What is incentivized also matters. The incentive to increase loan counts did not fully translate into commensurate increases in short term loan volumes. Incentives likely need to target both outcomes to achieve both, as agents may face tradeoffs between pursuing client counts and larger loans.

There are also open questions about the sustainability of incentives, as agents may become desensitized once incentives are no longer new or it may become progressively more difficult to respond as the client base may become saturated. There also remains substantial scope to test if effects could be maintained by mainstreaming WSME targets into key performance goals or efforts to cultivate lending norms.

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ACKNOWLEDGEMENTS AND DISCLOSURE

A portion of Markus Taussig and Russell Toth's time on the study, and other research costs (travel) were supported through consultancies funded and managed by the Asian Development Bank. The consultancies commissioned the authors to carry out an independent impact evaluation of the study intervention. Both authors negotiated for full rights to independently publish the results of the study.

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APPENDIXES

Incentivizing Inclusion: Experimental Evidence on Lending to Women-Led Firms in Vietnam

David A. Raitzer, Markus Taussig, and Russell Toth

March 26, 2026

APPENDIX A1: DESCRIPTIVE TABLES

Table A1: Monthly Individual Award Value for Each Contest Category (D)

	Top Winners	Most Improved Lenders	Best New WSME Lenders
Group 1 (4 branches)			
1st prize	3,500,000	2,500,000	2,500,000
2nd prize	3,000,000	2,000,000	2,000,000
3rd prize	2,500,000	1,500,000	1,500,000
4th prize	2,000,000	1,500,000	1,500,000
5th prize	2,000,000	1,500,000	1,500,000
6th prize	1,500,000		
7th prize	1,500,000		
8th prize	1,500,000		
9th prize	1,500,000		
10th prize	1,500,000		
Group 2 (12 branches)			
1st prize	3,500,000	2,500,000	2,500,000
2nd prize	3,000,000	2,000,000	2,000,000
3rd prize	2,500,000	1,500,000	1,500,000
4th prize	2,000,000		
5th prize	2,000,000		

Source: Authors.

Table A2: Award Availability and Actual Distribution, By Month

	Number of Awards Available			Number Actually Awarded		
	Top Winners	Most Improved	Best New	Top Winners	Most Improved	Best New
Group 1 (4 branches)						
February, 2024	10	5	5	4	1	1
March, 2024	10	5	5	11	1	5
April, 2024	10	5	5	10	5	5
May, 2024	10	5	5	10	1	3
June, 2024	10	5	5	11	2	5
July, 2024	10	5	5	10	1	5
Group 2 (12 branches)						
February, 2024	5	3	3	3	0	2
March, 2024	5	3	3	7	0	3
April, 2024	5	3	3	7	0	3
May, 2024	5	3	3	7	0	3
June, 2024	5	3	3	7	0	3
July, 2024	5	3	3	7	0	3

Note: Most Improved refers to most improved lenders. Best New refers to best new WSME Lenders. Actual award counts can exceed planned availability due to ties.
Source: Authors.

Table A3: Branch Incentive Awards

Award Name	Criteria	Quarterly Awards	Number of Awards in 6 Months	Amount (D)
For 8 treatment branches in Group 1				
Top 3 branches with highest total scores	Sum of total scores of all sales agents in the business team (including both official and probation staff)	3	6	1st: 15,000,000 2nd: 10,000,000 3rd: 5,000,000
			Total amount in 6 months	**60,000,000**
For 24 treatment branches in Group 2				
Top 7 branches with highest total scores	Sum of total scores of all sales agents in the business team (including both official and probation staff)	7	14	1st: 8,000,000 2nd: 6,000,000 3rd: 5,000,000 4th: 4,000,000 5th: 3,000,000 6th: 2,500,000 7th: 2,000,000
			Total amount in 6 months	**61,000,000**

Source: Authors.

Table A4: Head of Branch Awards

Award Name	Criteria	Quarterly Awards	Number of Awards in 6 Months	Awards (D)
For 8 treatment branches in Group 1				
Top one head of branch with the highest score	Average scores of all sales agents the branch	1	2	5,000,000
			Total amount in 6 months	**10,000,000**
For 24 treatment branches in Group 2				
Top one head of branch with the highest score	Average scores of all sales agents in branch	1	2	5,000,000
			Total amount in 6 months	**10,000,000**

Source: Authors.

APPENDIX A2: BALANCE CHECKS

Table A5: Balance Between Treatment Arms and Between Control and Treatment in the Pretreatment Period

	Relative to Control		Relative to Treatment 2	
	Coeff.	**p-val.**	**Coeff.**	**p-val.**
Monthly avg. # new micro-loans				
T1: Contest	-0.11	0.438	0.12	0.416
T2: Piece rate	0.01	0.929		
Monthly avg. # new unsecured micro-loans				
T1: Contest	-0.05	0.208	0.07	0.184
T2: Piece rate	0.02	0.647		
Monthly avg. # new secured micro-loans				
T1: Contest	-0.06	0.618	0.05	0.687
T2: Piece rate	-0.01	0.807		
Monthly avg. # new micro-loans to women SMEs				
T1: Contest	-0.02	0.473	0.01	0.711
T2: Piece rate	-0.01	0.644		
Monthly avg. # new unsecured micro-loans to women SMEs				
T1: Contest	-0.02	0.233	0.01	0.568
T2: Piece rate	-0.01	0.655		
Monthly avg. # new secured micro-loans to women SMEs				
T1: Contest	-0.00	0.862	0.00	0.928
T2: Piece rate	-0.00	0.892		
Monthly avg. # new micro-loans to men SMEs				
T1: Contest	-0.06	0.582	0.09	0.386
T2: Piece rate	0.03	0.579		
Monthly avg. # new unsecured micro-loans to men SMEs				
T1: Contest	-0.01	0.707	0.05	0.155
T2: Piece rate	0.04	0.253		
Monthly avg. # new secured micro-loans to men SMEs				
T1: Contest	-0.05	0.597	0.05	0.601
T2: Piece rate	-0.00	0.951		
Female staff				
T1: Contest	0.07	0.324	0.01	0.746
T2: Piece rate	0.08	0.249		

avg. = average, Coeff. = coefficient, p-val. = p-value, SME = small and medium-sized enterprise, T1 = Treatment 1, T2 = Treatment 2.

Notes: Columns 2–3 report coefficient estimates and p-values for t-tests comparing each treatment arm to the control group. Columns 4–5 report coefficient estimates and p-values for a t-test comparing Treatment 2 to Treatment 1. Standard errors are clustered by branch.

Source: Authors' calculations.