Targeting credit through community members

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Motivation

- Community-based approaches to target government benefits are widespread in developing countries.
  - Supporters: Community members may have relevant information.
  - Critics: Prone to favoritism.
- This tension can be stronger when:
  - Beneficiary attributes are costly to verify (e.g., productivity, risk).
  - Targeting entails balancing multiple criteria (e.g., neediness vs. productivity)
- However, exchanges in secondary markets could attenuate some targeting errors.

Three key questions

Context: Million Baht Village Fund (Thailand).

- Local committees allocate loans from government-donated credit funds.

1. What predicts selection program borrowing?
   - Risk? Poverty? Productivity? **No.**
   - Connections with local leaders? **Yes.**

2. Can local credit markets offset potential targeting distortions? **Yes, but only partially.**

3. How does the allocation achieved by community members compare to other counter-factual allocations? **Nuanced view.**

This paper...

1. Studies selection into credit based on pre-program characteristics.
   - Uses the Townsend-Thai monthly survey.
   - Neediness, TFP, risk, and connections to local elites.
2. Tests for indirect effects on households with reduced access to the program.
   - Outcome: borrowing from informal lenders.
   - Quasi-experimental variation: program rollout.
3. Analyzes the potential gains/costs from two counterfactual scenarios:
   - Eliminating the connections-based advantage.
   - Allocating credit based on a scoring model.

Results

- Credit was not allocated based on poverty, productivity or repayment.
- Instead, credit was disproportionately allocated to households with connections with local leaders.
- However, credit was indirectly delivered to unconnected households through informal credit markets.
- Despite the targeting frictions, the decentralized approach could be more appealing than a centralized approach based on hard information.

Context

The Million Baht Village Fund program (MBVF)

1. Main objectives:
   - Increase access to credit, promote income generation and provide relief to households in need.
2. Government donated credit funds to rural villages (VFs).
   - THB 1 million per village (USD 22,500) between 2001-2002.
3. Loan characteristics/Regulations:
   - On average low-interest loans: Program 7% $<$ Bank loans 9%.
   - Individual-liability and short term loans ($<$12 months).
   - Cosigner needed, no collateral.
   - Loan size cap: USD 450 (30% annual consumption).
4. Government incentives for well-performing villages:
   - Carrot: expansion of Village Funds.
   - Stick: Suspension of other transfers from central Gov.

The program's governance

1. Managed by an elected village fund committee (VFC).
   - Decides who obtains credit and loan conditions.
2. Village fund committee:
   - 9-15 community members.
   - Received a nominal remuneration.
   - Two-year term (re-election is possible).
   - Of legal age, with no criminal background, capable and respected (according to the village)
3. VF committee reports to the program's central office (*de jure* independent of local government)

Caveat: No data on membership to VFCs, only on membership to the local government (village chief and council members).

Village Fund Committees and the local political Elite

Village council (local government):

- Village chief and advisors.
- Smallest political unit in Thailand.
- Elected officials usually serving until retirement age.

Village Funds could be subject to elite capture:

- Village council is in charge of conflict resolution.
- Village council relatives or members themselves could be part of VFCs.

This paper: Focuses on the role of the local elite.

Data: The Townsend-Thai monthly survey

- 700 households, 16 villages, 4 provinces in Northeast Thailand.
  - Mostly entrepreneurs.
- Pre-program data: 2-3 years.
- Post-program data: 10-11 years.
- Information:
  1. Household financial accounts:
     - Balance sheets and income statements.
  2. Socio-economic Networks.
     - Kinship and transactions.
  3. Self-reported loan data:
     - Stream of disbursements and payments.

More.

Who obtains more program credit?

Selection into the program

VFCs stated objective:

- Promote income generation and provide relief to needy households.
- Guarantee the sustainability of funds.

Suggests that neediness, TFP and risk are relevant targeting criteria.

Do village-fund loans reach the needy?

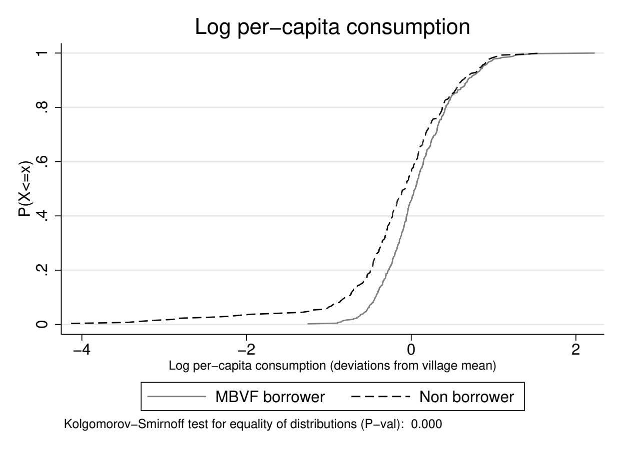


Figure: Program participation and baseline per-capita consumption

Distributions are standardized with respect to the village mean and s.d.

Do village-fund loans reach the most productive?

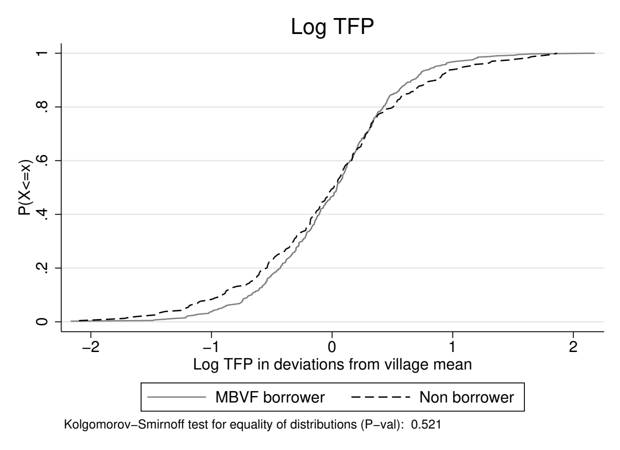
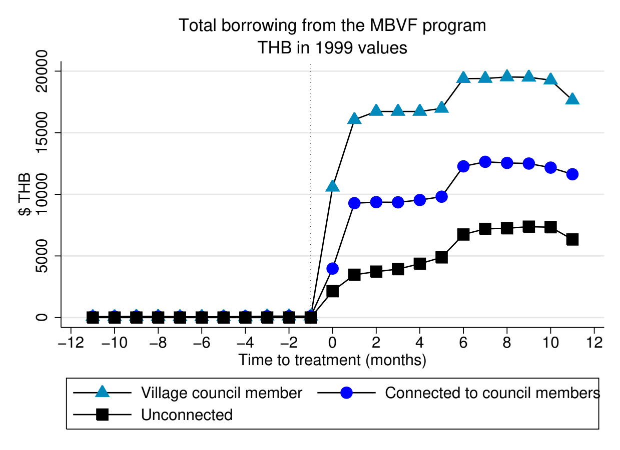


Figure: Program participation and baseline TFP

Distributions are standardized with respect to the village mean and s.d. Estimation Validation

Do elite-connected hhs select into the program?



Elite: Village Council (Village chief+advisors). Directly connected: based on pre-program transactions networks.

Baseline characteristics and program borrowing

Panel A: Correlates of MBVF borrowing and baseline characteristics (Mean MBVF borrowing: THB 10192)								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Per-cápita consumption (logs)	4,439***						3,680***	4,211***
	(981)						(1,036)	(1,161)
TFP (logs)			-501				-806**	-849**
			(339)				(326)	(331)
Access to institutional credit (dummy)				6,123***			4,695***	3,739***
				(848)			(904)	(932)
Ever missed a payment (dummy)					2,874***		1,460	1,321
					(1,056)		(1,051)	(1,046)
Connected with Village Council						2,793***	1,957**	1,975**
						(912)	(883)	(865)
Observations	650	652	619	652	652	652	617	614
Adjusted R-squared	0.233	0.203	0.203	0.255	0.210	0.213	0.276	0.303
Within-village R-Squared	0.040	0.001	0.003	0.066	0.010	0.014	0.096	0.132
Excludes HH with no credit history	No	No	No	No	No	No	No	No
Controls (demographics)+shocks	No	No	No	No	No	No	Yes	Yes

*** $p < 0.01$, ** $p < 0.05$, *$p < 0.1$

Standard errors are clustered at the household level. $***p < 0.01$, $**p < 0.05$, $*p < 0.1$.

Prob. of borrowing Repayment

The role of connections

Elite capture or network position?

Simply accounting for network centrality reduces the correlation between elite connections and VF borrowing.

	Panel A: Average MBVF borrowing (Mean: THB 10192)							
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Social Connections								
Connectedness with Village Council	2,793***	1,980**	195	467				
	(912)	(864)	(955)	(911)				
Village Council member					8,229***	5,646***	4,849***	3,724**
					(1,645)	(1,637)	(1,634)	(1,624)
Directly transacted with council member					1,931**	1,391	-388	16
					(979)	(925)	(998)	(956)
First-degree relative to council member					316	625	573	541
					(1,216)	(1,169)	(1,146)	(1,157)
Degree (count of links)			362***	238***			336***	230***
			(59)	(55)			(60)	(55)
Observations	652	614	652	614	652	614	652	614
Control for demographics	NO	YES	NO	YES	NO	YES	NO	YES
LASSO selection	NO	NO	NO	YES	NO	NO	NO	YES
Adjusted R-squared	0.21	0.30	0.27	0.32	0.24	0.31	0.28	0.33
Within-village adjusted R2	0.01	0.13	0.08	0.16	0.04	0.14	0.10	0.16

Standard errors are clustered at the household level. $***p < 0.01$, $**p < 0.05$, $*p < 0.1$.

Prob. of borrowing

However, being part of the local elite (Village Council) still predicts program borrowing.

Better enforcement or favoritism?

Insight: Favoritism should be costly to the lender.

$$\begin{aligned}\text{Return}_{kijt} = \quad & borrower_i + lender_j + \beta Connected_i \times MBVF_j \\ & +\Gamma_1 X_{ijt-1} + \Gamma_2 X_{ijt-1} \times MBVF_j + \epsilon_{kijt}\end{aligned}$$

- $Return_{kijt}$: *ex post* internal rate of return for loan k obtained in t.
- $MBVF$: VF loan.
- β: difference in relative returns from program loans with respect to comparison loans between connected and unconnected households.
- Favoritism: $\beta < 0$.

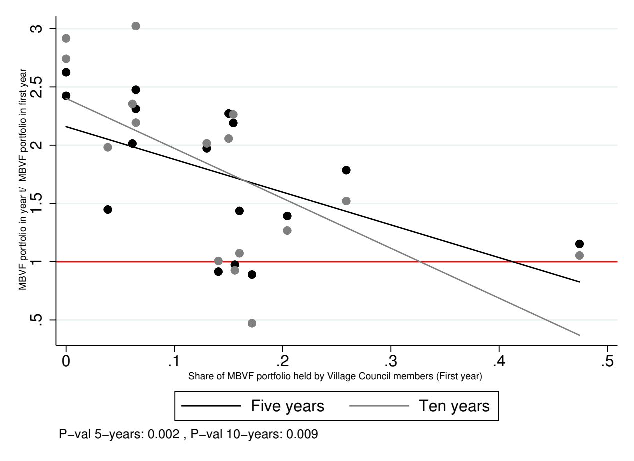
Lower ex-post returns to program loans wrt comparison loans

DV: IRRs (returns to the lender)				
	All loans		Private consumption	
	(1)	(2)	(3)	(4)
Connected X MBVF	-0.029**		-0.025**	
	(0.011)		(0.009)	
Direct connection X MBVF		-0.027**		-0.022**
		(0.010)		(0.009)
Council member X MBVF		-0.045***		-0.042***
		(0.015)		(0.012)
Observations	6,050	6,050	4,269	4,269
R-squared	0.190	0.191	0.246	0.248
Mean DV (Other Non VF)	0.0739	0.0739	0.0747	0.0747
P-val (Diff)		0.0316		0.00253

Standard errors are clustered at the lender j level. $***p < 0.01$, $**p < 0.05$, $*p < 0.1$.

Lower returns to loans to elite-connected households linked to lower initial IRs (More).

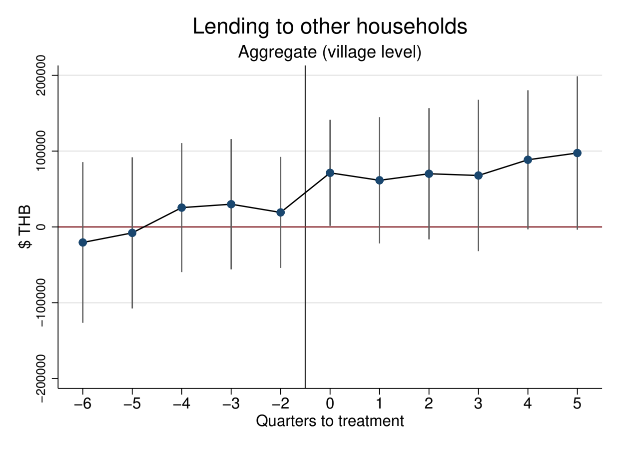
Loans to the elite as a survival strategy?



Village Funds that initially lent more to the elite grew less (some even contracted)

Key question: Can secondary transactions attenuate targeting distortions?

Program rollout and informal lending



Increase in total lending to other households increases after the program is introduced

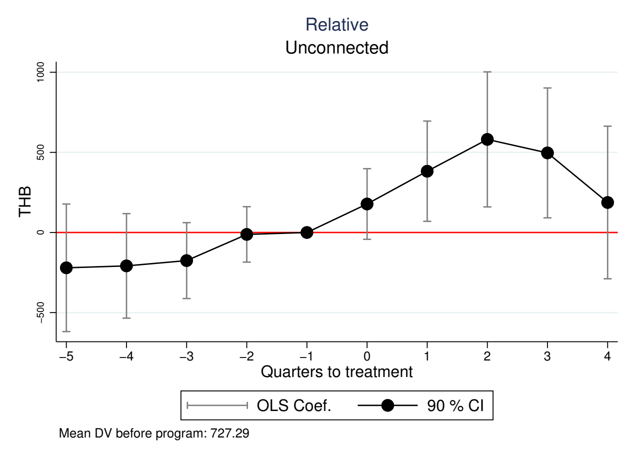
Can informal credit markets attenuate targeting distortions?

1. Intuition:
   - Unconnected households obtain less program credit due to targeting frictions.
   - Other well-informed lenders should be willing to serve unconnected households.
2. Empirical approach:
   - Event-study approach using the staggered program rollout across villages.

$$Relatives_{ivt} = \alpha_i + \delta_t + \beta Post_{v,t} + \epsilon_{ivt} \tag{1}$$

- α_i, δ_t: Household and time fixed effects.
- $Post_{vt}$: Post period.
- Split sample between connected and unconnected.

Effects of the program on borrowing from relatives



CI based on wild bootstrap-t correction for small number of clusters (villages). Equation

Unconnected households more likely to borrow from relatives

	Total borrowing			Prob. of borrowing		
	All	Connected	Unconnected	All	Connected	Unconnected
Post$_{vt}$	224**	144*	424*	0.010	-0.002	0.033*
Bootstrap p-value	[0.024]	[0.091]	[0.064]	[0.372]	[0.916]	[0.080]
Observations	23,013	15,030	7,983	23,228	15,143	8,085
R-squared	0.681	0.740	0.555	0.640	0.680	0.559
P-val (Connected-Unconnected)		[0.22]			[0.068]	
Baseline DV mean	592	623.8	532.1	0.0707	0.0733	0.0658
# of households	671	439	232	671	439	232

Inference based on Cameron et.al(2008) wild bootstrap-t procedure to account for small number of clusters (villages).$p < 0.01$,**$p < 0.05$,*$p < 0.1$.

Effects account for $\sim$ 11% of program's gap based on connections.

Average annual interest rate associated to loans from relatives: 12%. (Lending)

Are there gains from reallocation?

- Two counterfactuals:
  - Counterfactual allocation eliminating excess borrowing due to connections.
  - Counterfactual allocation based on scoring model.
- Compute changes in social welfare and inequality (consumption - CRRA utility).
- Use production function estimates to quantify gains from reallocation.

Gains from eliminating the connection based advantage.

Details

Eliminating the connection-based advantage decreases inequality and modestly increases output.

Eliminating the connection-based advantage

Social welfare and inequality			
% Change in welfare (negative changes denote improvements)*		-9.8%	
% Change in inequality		-9.7%	
	$\kappa = 1$	$\kappa = 0.61$	$\kappa = 0$
Output			
% Output gains	0.0%	0.9%	1.5%

*CRRA utility parameter $\rho = 3$. κ : Share of credit allocated to investment in fixed capital (K).

Consistent with VFCs providing more credit to wealthier, connected households.

Community-based vs. centralized targeting

A centralized score would eliminate the connection advantage but would target credit at wealthier households: ↑ Inequality and very modest increase in output. (Details)

Reallocation from overincluded to overexcluded households (scoring model)			
Social welfare and inequality			
% Change in welfare (negative changes denote improvements)*		148%	
% Change in inequality		19.6%	
	$\kappa = 1$	$\kappa = 0.61$	$\kappa = 0$
Output			
% Output gains	1.3%	1.7%	1.5%

*CRRA utility parameter $\rho = 3$. κ : Share of credit allocated to investment in fixed capital (K).

Concluding remarks

1. Community-based approaches to target credit can suffer from connection-based allocative distortions.

2. Markets may partially attenuate targeting distortions, but at higher prices.

3. Despite the targeting errors, a decentralized approach may be more appealing than a centralized approach.

Policy considerations:

- Improving incentives for local committees.
- Responses in secondary markets may need to be considered for program design.

Some ongoing work

- Heterogeneous effects of credit and misallocation.
  - Use baseline productivity to predict returns to credit from MBVF.
- How local networks serve the dual role of providing insurance but spreading shocks.

Thank you!

Pre-program household characteristics

- 55% of households borrowed from institutional lenders.
  - Loan size: 25% of yearly per-capita consumption.
- 35% of households reported borrowing from informal lenders.
- On average household have 3-4 sources of income:
  - 74% of households obtain income from agriculture.
  - 78% from wages.
  - 32% from off-farm businesses, 65% livestock, 45% Fishing.

Back.

TFP Estimation

Cobb-Douglas gross-revenue function.

$$
\begin{aligned}
y_{i,t} &= \omega_{i,t} + \beta_k k_{i,t} + \beta_m m_{i,t} + \beta_l l_{i,t} + \epsilon_{i,t} \\
\omega_{i,t} &= a_i + \rho\omega_{i,t-1} + \zeta_{i,t}
\end{aligned}
$$

- y=Revenues, k=stock of fixed assets, m=Inputs, l=labor.
- ω= TFP.

Backing out TFP:

- Estimate $\beta_k, \beta_m, \beta_l$ using GMM (Blundell & Bond (1998)) using 14 years of data. (assuming pf is constant over time)
- Allow for different elasticities between farm and nonfarm sectors.
- Use **pre-program** (y,k,m,l) to back out pre-program TFP.

Back

Pre-program TFP correlates with shocks and hh characteristics

	Measured TFP	
	(1) Farm	(2) Non Farm
Age of household's head	-0.00	0.00
	(0.00)	(0.01)
Household's head completed primary school	0.10	0.27**
	(0.09)	(0.13)
Head of household gender (male)	0.09	0.08
	(0.09)	(0.09)
Number of adults	0.00	-0.03
	(0.05)	(0.08)
Number of elder	0.04	0.06
	(0.03)	(0.05)
Number children under 5	0.02	0.00
	(0.05)	(0.07)
Share of females in the household	-0.16	-0.12
	(0.17)	(0.29)
Average age in household	-0.01	-0.00
	(0.00)	(0.01)
Average education level in household	0.01	0.01
	(0.02)	(0.03)
Count of health symptoms	0.01**	-0.00
	(0.00)	(0.00)
Count of shocks to non farm business	-0.01	-0.01
	(0.01)	(0.02)
Count of shocks to livestock business	0.01	0.02
	(0.01)	(0.03)
Count of shocks to agriculture	-0.04*	-0.01
	(0.02)	(0.03)
Share of agricultural revenues	3.81***	-1.39
	(1.31)	(1.72)
Share of agricultural revenues X rainfall	7.17***	-1.08
	(2.48)	(3.11)
Idiosyncratic Return over Assets	0.01*	0.02***
	0	(0.01)
Observations	292	228
R-Squared	0.45	0.54
Adjusted R-squared	0.38	0.46

*** p<0.01, ** p<0.05, * p<0.1

Back

Production function estimates

	(1) Farm	(2) Non Farm
ρ	0.66***	0.72***
	(0.06)	(0.03)
β_k	0.15***	0.26***
	(0.06)	(0.09)
β_m	0.40***	0.33***
	(0.04)	(0.04)
β_l	0.14***	0.28***
	(0.04)	(0.08)
Obs	3584	2586
J-stat OID-OMD	1.69	1.70
P-val (OID-OMD)	0.64	0.64

$***p < 0.01, **p < 0.05, *p < 0.1$

Back

Empirical specification

$$Relatives_{ivt} = \alpha_i + \delta_t + \sum_{j=-6, j \neq -1}^{j=6} \beta_j \mathbb{I}[\tau_{vt} = j] + \epsilon_{ivt} \qquad (2)$$

- α_i: Household fixed effects.
- δ_t: Calendar month and year fixed effects.
- τ_{vt}: Time to treatment.
- Split sample between connected and unconnected.

Back

Baseline characteristics and access to MBVF credit

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Per-capita consumption (logs)	0.159***						0.104***	0.132***
	(0.025)						(0.035)	(0.040)
TFP (logs)			0.013				-0.004	-0.006
			(0.014)				(0.014)	(0.014)
Access to institutional credit (dummy)				0.342***			0.232***	0.211***
				(0.041)			(0.049)	(0.052)
Ever missed a payment (dummy)					0.149***		0.032	0.022
					(0.047)		(0.049)	(0.049)
Connected with Village Council						0.163***	0.097**	0.093**
						(0.043)	(0.045)	(0.045)
Observations	692	710	648	710	710	710	646	642
Adjusted R-squared	0.110	0.079	0.071	0.161	0.082	0.091	0.143	0.146
Within-village R-Squared	0.040	0.009	0.000	0.097	0.011	0.021	0.078	0.083
Excludes HH with no credit history	No	No	No	No	No	No	No	No
Controls (demographics)+shocks	No	No	No	No	No	No	Yes	Yes

*** $p < 0.01$, ** $p < 0.05$, *$p < 0.1$

Standard errors are clustered at the household level. $***p < 0.01$, $**p < 0.05$, $*p < 0.1$. Back

Credit history and program borrowing

Correlates of program credit and Risk and credit history

	OLS Coefficient (1)	S.E. (Diff) (2)	P-val (3)	Hochberg Adj-Pval (4)
Ever borrowed from institutional lender	6,123***	(848)	0.00	0.00
Leverage rate	5,033	(3,443)	0.14	0.58
Income volatility (log coef. of variation)	-686	(640)	0.28	0.85
Share of loans with delinquent payments	-698	(2,566)	0.79	0.79
Missed a payment (dummy)	1,885*	(1,086)	0.08	0.42
Share of loans with term extensions	1,059	(1,465)	0.47	0.94
Extended loan (dummy)	2,734**	(1,127)	0.02	0.09

Back

Elite capture or network position?

	Panel B: Borrowed from the program (dummy - Mean: 0.58)							
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Social Connections								
Connectedness with Village Council	0.16***	0.10**	0.07	0.08*				
	(0.04)	(0.05)	(0.05)	(0.05)				
Village Council member					0.32***	0.18***	0.18***	0.16**
					(0.06)	(0.07)	(0.07)	(0.07)
Directly transacted with council member					0.15***	0.08*	0.06	0.07
					(0.05)	(0.05)	(0.05)	(0.05)
First-degree relative to council member					-0.02	0.04	-0.00	
					(0.06)	(0.06)	(0.05)	
Degree (count of links)			0.01***	0.01***			0.01***	0.01***
			(0.00)	(0.00)			(0.00)	(0.00)
Observations	710	642	710	691	710	642	710	691
Control for demographics	NO	YES	NO	YES	NO	YES	NO	YES
LASSO selection	NO	NO	NO	YES	NO	NO	NO	YES
Adjusted R-squared	0.09	0.15	0.14	0.21	0.10	0.15	0.14	0.21
Within-village adjusted R2	0.02	0.09	0.07	0.14	0.03	0.09	0.07	0.15

$***p < 0.01, **p < 0.05, *p < 0.1$

Standard errors are clustered at the household level. $***p < 0.01$, $**p < 0.05$, $*p < 0.1$. Back

Differences in loan characteristics and outcomes

Panel A: Differences by connectedness (All loans)

	(1) *Ex post* IRR (annual)	(2) Any delinquent payment	(3) Term extension	(4) IR (initial)	(5) Term (months)	(6) Amount (THB)	(7) Loan > max. amount
Connected X MBVF	-0.029**	-0.010	-0.031	-0.015*	0.837	1,554.539*	0.018
	(0.011)	(0.009)	(0.020)	(0.008)	(0.560)	(914.850)	(0.014)
Observations	6,050	5,484	6,072	6,072	6,072	6,117	6,117
R-squared	0.190	0.158	0.300	0.341	0.316	0.701	0.383
Mean DV (Other)	0.0739	0.0133	0.391	0.0610	12.28	3933	0.0128

Panel B: Differences by type of connection (All loans)

	(1) *Ex post* IRR (annual)	(2) Any delinquent payment	(3) Term extension	(4) IR (initial)	(5) Term (months)	(6) Amount (THB)	(7) Loan > max. amount
Direct connection X MBVF	-0.027**	-0.012	-0.028	-0.014*	0.812	1,395.588	0.011
	(0.010)	(0.009)	(0.018)	(0.008)	(0.566)	(879.570)	(0.012)
Council member X MBVF	-0.045***	-0.000	-0.051	-0.017**	0.980	2,489.862*	0.057
	(0.015)	(0.009)	(0.054)	(0.008)	(0.728)	(1,285.686)	(0.037)
Observations	6,050	5,484	6,072	6,072	6,072	6,117	6,117
R-squared	0.191	0.158	0.300	0.341	0.316	0.701	0.384
P-val (Direct Connection - Council Member)	0.0316	0.143	0.648	0.469	0.765	0.184	0.155
Mean DV (Other)	0.0739	0.0133	0.391	0.0610	12.28	3933	0.0128

Standard errors clustered at the lender level. Back

Evidence of re-lending

Table: Effects on lending to other households

	Total Lending			Prob. of Lending		
	All	Connected	Unconnected	All	Connected	Unconnected
$Post_{v,t}$	497	568	544	0.019**	0.021*	0.015
Bootstrap p-value	[0.176]	[0.400]	[0.156]	[0.020]	[0.044]	[0.236]
Observations	23,783	15,522	8,261	25,560	16,488	9,072
R-squared	0.834	0.870	0.647	0.791	0.784	0.805
P-val (Connected-Unconnected)		[0.976]			[0.676]	
Baseline DV mean	4888	6023	2764	0.225	0.239	0.200
# of households	685	444	241	710	458	252

Inference based on Cameron et.al(2008) wild bootstrap-t procedure to account for small number of clusters (villages).$p < 0.01$,$p < 0.05$,*$p < 0.1$.**

Back.

Eliminating elite advantage

- Recall: Connected households get on average THB **1,982** more program credit (controlling for a full set of covariates).
- Add the total excess lending due to connections (village level).
- Reallocate credit:
  - From **A:** Connected households.
  - To **B:** non-borrowers (equal share).

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Allocation based on predicted risk

- Estimate a model of repayment based on pre-program credit history, household balance sheets, and demographics (LASSO).
- Apply estimates to all potential borrowers.
- 34% of program borrowers would be ineligible based on repayment.
- Add the total lending amount to would-be ineligible hhs.
- Reallocate credit:
  - From **A:** low-repayment program borrowers (poorer).
  - To **B:** high-repayment, non-borrower households (equal share).

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