ECON 326: Economics of Developing Countries
TA Session 7

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May 2025

Today's Agenda

- Beaman, Karlan, Thuysbaert & Udry (2023)
- Feigenberg, Field, & Pande (2013)
- Karlan and Zinman, (2009)

Beaman, Karlan, Thuysbaert & Udry (2023)

Selection Into Credit Markets: Evidence from agriculture in Mali

Overview

- Returns to investment in productive activities may be heterogenous

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- Market failures in financial and credit markets could impede efficient allocation of capital
- This paper examines the extent to which a lending program for smallholder farmers in Mali successfully identifies and allocates credit to the farmers with higher returns to investment

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- Stage 2: After decisions to take up the loan were made, a random subset of households that did not borrow in loan villages and in non-loan villages were immediately given a cash grant
- Key idea: identify whether those who chose not to borrow have lower average returns to a grant

RCT Design II

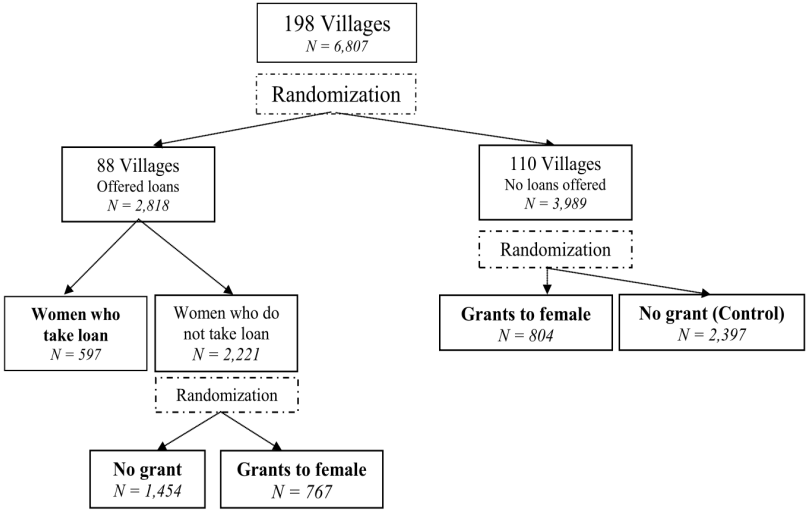

FIGURE 1.—Experimental design: allocation of households to treatments.

Strategy

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- $loan_{v(i)} = 1$ if household i is in a village $v(i)$ that gets loans (but if so, this means i got shut out of the credit market)
- β_1 is the effect of the cash grant in non-loan villages
- β_2 is the additional effect of the cash grant on households from loan villages denied loans (for them, the total effect of cash grants is $\beta_1 + \beta_2$)

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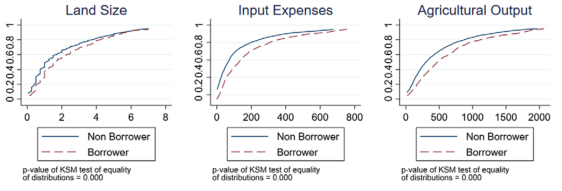

FIGURE 3.—Baseline characteristics of borrowers versus non-borrowers in loan villages.

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- In both loan and no-loan villages, grant recipients increase consumption
- But effects on recipients' economic performance, as measured by their farms' profits, are only observed in no-loan villages
- Suggests that those not selected into credit have lower profitability: receiving money does not raise their profits too much

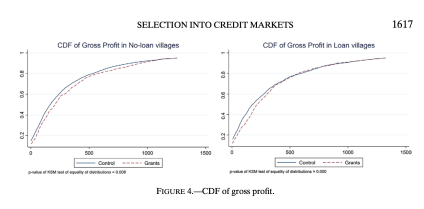

FIGURE 4.—CDF of gross profit.

Results III

TABLE II

AGRICULTURE—YEAR 1.

	Land cultivated (ha)	Land planted with rice and groundnut (ha)	Used plough (0/1)	Quantity seeds (Kg)	Family labor (days)	Hired labor (days)	Fertilizer and chemical expenses (USD)	Total input expenses (USD)	Value agricultural output (USD)	Gross Profit (USD)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Grant β_1	0.26	0.09	0.06	7.32	6.49	3.22	24.06	34.39	74.73	42.77
	(0.07)	(0.02)	(0.01)	(2.49)	(4.55)	(0.99)	(6.85)	(8.84)	(21.46)	(16.84)
	[0.000]	[0.000]	[0.000]	[0.004]	[0.111]	[0.000]	[0.000]	[0.000]	[0.000]	[0.002]
Grant * loan village β_2	−0.22	0.01	0.00	0.85	−5.85	2.03	−19.74	−16.49	−53.95	−43.05
	(0.11)	(0.04)	(0.02)	(4.02)	(7.00)	(1.60)	(9.47)	(12.81)	(30.11)	(23.18)
	[0.023]	[0.875]	[0.936]	[0.820]	[0.348]	[0.126]	[0.039]	[0.184]	[0.203]	[0.239]
p-value for $\beta_1 + \beta_2 = 0$	0.637	0.001	0.001	0.010	0.905	0.000	0.507	0.054	0.327	0.986
N	5393	5440	5393	5392	5393	5393	5440	5393	5392	5392
Mean of control (year 1)	2.15	0.90	0.80	91.16	140.54	18.02	125.64	196.24	526.74	330.51
SD of control (year 1)	2.38	0.78	0.40	83.51	140.99	25.39	221.74	275.56	660.14	475.35
Per $100 impact for loan takers	0.77	0.05	0.05	2.95	20.35	−3.14	70.23	68.88	198.35	146.24
	(0.32)	(0.11)	(0.07)	(11.97)	(21.06)	(4.77)	(29.19)	(39.05)	(92.45)	(71.48)

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- So is it okay that these households are excluded from the credit market?

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- Learning more from evaluations about treatment effects conditional on various methods of selection could provide critical information for forming optimal policy

Feigenberg, Field, & Pande (2013)

Building Social Capital Through Microfinance

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- This paper examines the role of repeated social interactions in building social capital

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  - Compliance with meeting protocol was high in Control and Treatment 1 groups, Treatment 2 had poor compliance rates

Randomisation Check

Table 1. Randomization Check

	All Clients			Lottery/Long-Run Survey Clients		
	Control Mean (Monthly-Monthly)	Treatment 1 (Weekly-Weekly)	Treatment 2 (Weekly-Monthly)	Control Mean (Monthly-Monthly)	Treatment 1 (Weekly-Weekly)	Treatment 2 (Weekly-Monthly)
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A						
Age	33.969	-0.593	-1.110	33.832	-0.806	-0.920
	(8.553)	(0.813)	(0.724)	(8.418)	(0.810)	(0.764)
Literate	0.865	-0.012	-0.059	0.880	-0.012	-0.059
	(0.342)	(0.035)	(0.039)	(0.325)	(0.036)	(0.040)
Married	0.862	0.013	0.005	0.871	0.025	-0.009
	(0.345)	(0.031)	(0.030)	(0.336)	(0.030)	(0.029)
Household Size	3.821	0.153	0.207*	3.903	0.068	0.106
	(1.335)	(0.106)	(0.114)	(1.357)	(0.119)	(0.124)
Muslim	0.023	-0.023	0.118**	0.026	-0.026	0.122*
	(0.151)	(0.021)	(0.060)	(0.159)	(0.023)	(0.062)
Years Living in	17.423	-2.010**	-0.931	17.136	-2.175**	-0.456
Neighborhood	(10.473)	(0.889)	(0.919)	(10.407)	(0.903)	(0.976)
Number of Clients	10.364	-0.086	-0.037	10.385	-0.073	-0.054
in Group	(0.727)	(0.185)	(0.192)	(0.741)	(0.199)	(0.196)
Group Formed	0.595	-0.147	-0.109	0.654	-0.154	-0.159
in Rainy Season	(0.492)	(0.122)	(0.120)	(0.477)	(0.124)	(0.119)
Heavy Rain Days	5.265	-0.128	-0.477	5.453	-0.205	-0.614
	(2.070)	(0.545)	(0.519)	(2.060)	(0.576)	(0.534)
Panel B						
Client Worked for	0.525	0.060	0.011	0.524	0.056	0.018
Pay in Last 7 Days	(0.500)	(0.053)	(0.053)	(0.500)	(0.053)	(0.053)
Household Earns	0.442	-0.079*	0.023	0.437	-0.065	0.048
Fixed Salary	(0.497)	(0.044)	(0.049)	(0.497)	(0.046)	(0.050)
Household Owns	0.717	0.038	-0.080	0.718	0.034	-0.085
Business	(0.451)	(0.049)	(0.061)	(0.450)	(0.053)	(0.061)
Household Savings	1636.2	325.7	1238.9	1828.7	103.3	1125.2
	(5793.7)	(564.8)	(762.9)	(6405.5)	(653.7)	(840.5)
Household Owns Home	0.808	-0.033	-0.035	0.828	-0.048	-0.047
	(0.395)	(0.044)	(0.047)	(0.378)	(0.046)	(0.048)
Education Expenditures	4183.9	559.5	-278.2	4490.2	112.0	-598.2
	(4868.2)	(407.8)	(356.3)	(4919.3)	(456.7)	(392.9)
Health Expenditures	3311.4	-35.0	-399.4	3241.4	-87.7	-226.9
	(5262.1)	(522.2)	(432.4)	(5154.4)	(562.9)	(432.1)
Illness in Past 12 Months	0.314	0.029	-0.080*	0.307	0.016	-0.062
	(0.465)	(0.048)	(0.046)	(0.462)	(0.053)	(0.049)
Number of Transfers into	1.388	0.172	-0.503	1.085	0.205	-0.185
Households	(6.796)	(0.542)	(0.449)	(4.659)	(0.362)	(0.335)
Number of Transfers out of	2.613	0.282	-0.253	2.563	0.311	-0.147
Households	(4.693)	(0.604)	(0.558)	(4.728)	(0.658)	(0.592)
Days between Loan				788.312	-0.211	13.977
Disbursement and Lottery				(46.182)	(11.360)	(10.968)
N	385	306	325	309	250	297

Meeting Frequency and Social Interactions

Table 2. Meeting Frequency and Social Interactions in the Short Run and Long Run

	Short Run	Long Run			
	Social Contact Index	Total Times Met	Attend Durga Puja	Talk Family	Social Contact Index
	(1)	(2)	(3)	(4)	(5)
Panel A: No Controls					
Treatment 1	3.005***	2.045**	0.069*	0.070*	0.186**
(Weekly-Weekly)	(0.107)	(1.001)	(0.038)	(0.039)	(0.080)
Panel B: Controls Included					
Treatment 1	3.052***	2.054**	0.081**	0.071**	0.199***
(Weekly-Weekly)	(0.092)	(0.891)	(0.039)	(0.035)	(0.073)
Control Mean (Monthly-Monthly)		5.475 [10.386]	0.153 [0.360]	0.229 [0.421]	
Specification	OLS	OLS	Probit	Probit	OLS
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Panel A: No Controls					
Treatment 1	3.005***	2.045**	0.069*	0.070*	0.186**
(Weekly-Weekly)	(0.107)	(1.001)	(0.038)	(0.039)	(0.080)
Panel B: Controls Included					
Treatment 1	3.052***	2.054**	0.081**	0.071**	0.199***
(Weekly-Weekly)	(0.092)	(0.891)	(0.039)	(0.035)	(0.073)
Control Mean (Monthly-Monthly)		5.475 [10.386]	0.153 [0.360]	0.229 [0.421]	
Specification	OLS	OLS	Probit	Probit	OLS
N	684	3026	3023	3026	3026

- Use survey to ask clients about how frequently they interact with group members at the end of meetings
- Switching a client from monthly to weekly meetings increases social contact with the group by over 3 sd.

Meeting Frequency and Social Interactions

Table 2. Meeting Frequency and Social Interactions in the Short Run and Long Run

	Short Run	Long Run			
	Social Contact Index	Total Times Met	Attend Durga Puja	Talk Family	Social Contact Index
	(1)	(2)	(3)	(4)	(5)
Panel A: No Controls					
Treatment 1	3.005***	2.045**	0.069*	0.070*	0.186**
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- Use survey to ask clients about how frequently they interact with group members at the end of meetings
- Switching a client from monthly to weekly meetings increases social contact with the group by over 3 sd.
- These differences are persistent

Risk-sharing

- The authors examine whether increased social interaction facilitated risk-sharing arrangements

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- Play field-based lottery games to elicit willingness to form risk-sharing arrangements

Risk-sharing

- The authors examine whether increased social interaction facilitated risk-sharing arrangements
- Play field-based lottery games to elicit willingness to form risk-sharing arrangements
- A client was chosen for the lottery and could choose to give tickets to other group members

Risk-sharing II

Table 3. Meeting Frequency and Risk-Sharing: Ticket-Giving and Transfers

	Main Lottery			Supplementary Lottery	Transfers		
	Gave Ticket						
	All	1-Rs. 200 Voucher	4-Rs. 50 Vouchers	All	Close Family/ Friend	Neighbor/ Other Relative	Other Non-Relative
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: No Controls							
Treatment 1 (Weekly-Weekly)	0.067** (0.034)	0.043 (0.041)	0.091* (0.048)	-0.005 (0.069)	0.016 (0.065)	0.122** (0.061)	-0.019 (0.028)
Group Member				0.068** (0.034)			
Treatment 1*Group Member				0.157** (0.079)			
Panel B: Controls Included							
Treatment 1 (Weekly-Weekly)	0.072** (0.033)	0.044 (0.039)	0.105** (0.048)	0.0001 (0.071)	0.019 (0.066)	0.126** (0.058)	-0.011 (0.024)
Group Member				0.073** (0.036)			
Treatment 1*Group Member				0.158* (0.081)			
Control Mean (Monthly-Monthly)	0.281 [0.450]	0.277 [0.448]	0.285 [0.452]	0.223 [0.417]	0.426 [0.495]	0.309 [0.463]	0.067 [0.250]
Specification	Probit	Probit	Probit	Probit	Probit	Probit	Probit
N	5282	2695	2587	847	651	651	651

- Column 1: Treatment 1 clients gave 23.8% more tickets than the Control group

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- Consistent with stronger social ties among clients who meet weekly translating into higher willingness to risk-share in the lottery game

Altruism or Reciprocity?

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- Randomise divisibility of prize
- Looks like people are doing it more for reciprocity than altruism

Loan Default

Table 4. Meeting Frequency and Default: Evidence from the Second Loan Cycle

	Default		Group Met Weekly	Default
	(1)	(2)	(3)	(4)
Panel A: No Controls				
Treatment 1	-0.052**	-0.052**		
(Weekly-Weekly)	(0.021)	(0.021)		
Treatment 2 (Weekly-Monthly)*Heavy Rain Days			-0.118***	
			(0.020)	
Treatment 2			1.086***	
(Weekly-Monthly)			(0.152)	
Heavy Rain Days			0.025	
			(0.016)	
Group Met Weekly				-0.077**
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- Second loan offered with same terms for both Control and Treatment 1 clients
- Columns (1) and (2): Treatment 1 clients nearly 3 times (5.2%) less likely to default on second loan relative to Control

Discussion

- A program that encourages repeat interactions increases long-run social ties

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Discussion

- A program that encourages repeat interactions increases long-run social ties
- Enhances social capital
- Improved risk-sharing in a setting where contract enforcement is weak $\rightarrow$ welfare-improving

Karlan and Zinman (2009)

Observing Unobservables: Identifying Information Asymmetries with a Consumer Credit Field Experiment

This paper

- Seminal work in the field of consumer finance in developing countries

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- RCT to study the effect of interest rates on default, summarized in the figure

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- Seeks to disentangle how interest rates affect default through (1) adverse selection, (2) moral hazard, (3) repayment burden

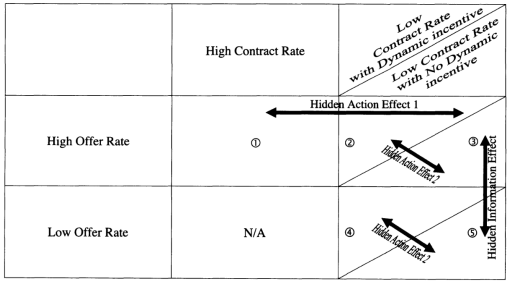
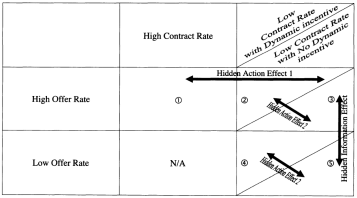


FIGURE 1.—Some basic intuition for our identification strategy.

Adverse Selection



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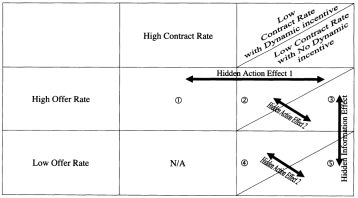

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- The paper tests whether interest rates affect default by screening out low-quality borrowers

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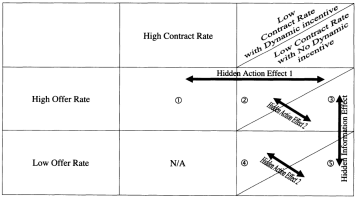

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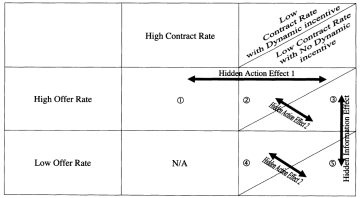

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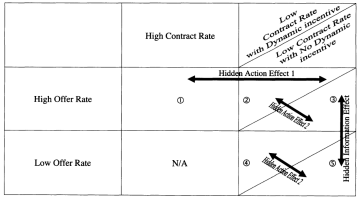

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- The paper tests whether interest rates affect default by screening out low-quality borrowers
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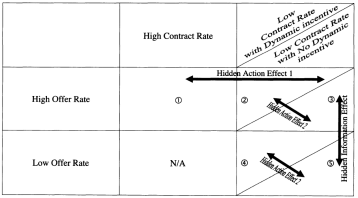
- These are pairs of groups who face the same contract rate and the same repayment incentives
- They only differ in the loan that was initially offered to them, which determined who accepted to participate in the study

Moral Hazard



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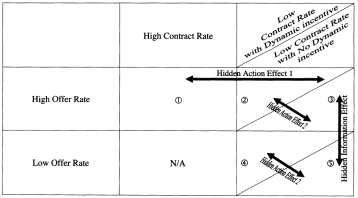

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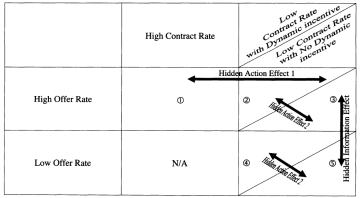

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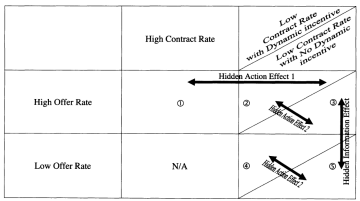

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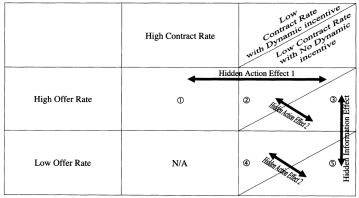

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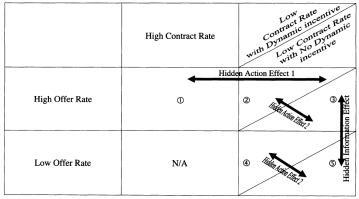

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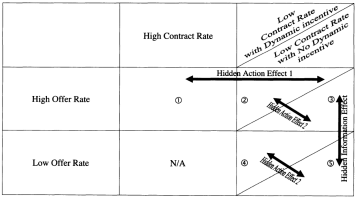
- To isolate this channel, compare 2 vs. 3 and 4 vs. 5
- These are pairs of groups with same offer and contract rates
- They differ in whether they receive a dynamic incentive: groups 2 and 4 are told that their future interest rate will depend on whether they default

Repayment Burden



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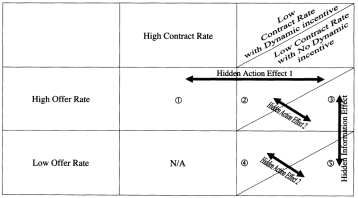

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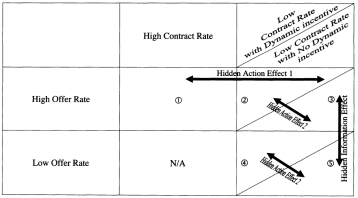

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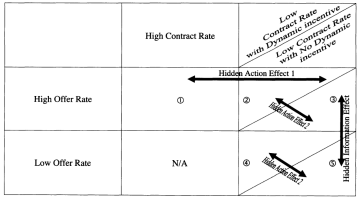

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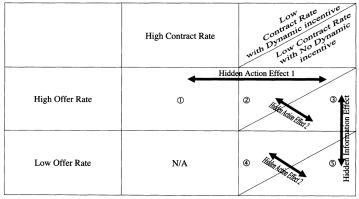

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- A higher contract rate (on group 1) has a cost effect: the loan becomes more difficult to pay off so default will mechanically go up
- But the higher contract rate affects the decision to default via moral hazard too: defaulting becomes more attractive