Appendix

Construct validity of loan officer typology

When instructing managers to code each loan officer by relational style, managers were show table 1 and told that the categories only referred to relational styles and not performance. Two things are worth mentioning. First, the managers thought it was descriptive, intuitive, and a fair representation of loan officers. Second, managers coded loan officers with remarkable speed. It typically took them less than one second to place an officer, which both reinforces the validity of the typology and reveals the depth with which managers know their staff. Inter-rater reliability was just below 80 percent. There was no instance where one manager coded an officer as SL while another coded her as LL. The only discrepancies were between a coherent type and Mixed. These discrepancies were treated as Mixed. The reason for doing so is straightforward: The inability of managers to agree on how to classify a loan officer provides *prima facia* evidence that the loan officer's style is inconsistent.

It should be noted that although there are clear behavioral and philosophical differences in enforcement styles, the qualitative evidence leads us to believe that the underlying motivation of officers is the same across types: to perform their jobs well, which means minimizing delinquencies under conditions of risk or uncertainty. For LL officers this entails deference to the parameters defined by organizational policies and contractual provisions. SL officers, on the other hand, seek to minimize information asymmetries by developing multiplex relationships that maximize information access, reduce risk or uncertainty, and create alternative enforcement avenues.

Differences in relational style are at no point more evident than in the case of a loan delinquency, which is a discrete event that must be documented pursuant to organizational policies. Loan officers are expected to collect the loan following contractual terms. Yet, while all missed payments look the same on paper –and clients give similar explanations for them—some loan officers choose to collect the loan as prescribed by the policies while others choose to engage in negotiations and problem solving with the client. The choice depends, most importantly, on the loan officer's reading of the reason behind the delinquency.

During one of the author's ethnographic fieldwork he observed that SL officers overwhelmingly chose to negotiate with clients who missed a payment while LL officers generally chose to collect following contractual terms and company policy. Loan officers typically visit between one and three missed-payment clients or groups per day. Between 2002 and 2008 a total of 578 loans were restructured through negotiation. SL officers restructured more than half of those loans, while LL officers only accounted for 100 restructurings. From each officer's perspective, however, the goal was simply to achieve a better business performance. Delinquency rates are the most highly weighted element of an officer's bonus and it is usually the first thing that managers look at when assessing loan officer performance. Thus when SL officers go out of their way—sometimes interpreting policies in expansive terms to "help" a client—they are not being altruistic. In fact, they are not equally "lenient" with all clients and their collection strategy is not based on compassion but on a different interpretive frame. Qualitative client interviews—especially with clients who dropped out of the program—revealed that the most common cause for missed payments is a client's vulnerability to external shocks. Poorer households are more sensitive to contingencies due to a lack of assets, savings, or support structures to absorb them (e.g. Morduch, 1994). All clients confront exogenous economic shocks at some point, but the more destitute have less of a buffer, so even small, unforeseen events can set-off a chain of negative consequences. In cases of clients who missed payments after a negative shock and the loan officer chose to support them through a restructuring or a contingency loan, they were often able to get back on their feet. When loan officers demanded repayment pursuant to contractual terms notwithstanding these shocks, she often hastened and exacerbated the downward cycle. Putting pressure on a good but troubled client often only leaves the option of informal moneylenders who can –and almost always do—create disastrous effects. Clients take out loans to pay other loans. Since they are not investing in productive activities, they become entangled in a trap. As an illustration, consider two women who started with loans of $50 and, after some productive loan cycles they became entangled in a debt spiral. One owed $50,000 and the other $25,000. The MFI's credit analysis determined a debt capacity of $300 for each, which should put their outstanding debt in some perspective. At the same time, the more vulnerable the client, the harder it is to codify her information in company policies, and the less guidance that a loan officer has to make decisions. In such situations, SL officers rely on personal relationships to gather additional information while LL officers fall back on the company's policies, which they trust:

> *If your client is in a bad situation […] and you don't find a solution for her, then you can turn good clients into bad ones. […] Whenever my poorer clients tell me they can't make a payment because something bad happened to them, I have a policy of always trusting them […] of every ten clients I have helped, nine have made it and eight have become long-term clients. A restructuring is a great opportunity because you develop a double commitment with your client. (SL officer)*

Contrast this with a representative LL officer's interpretation:

> *Clients are always trying to take advantage of the firm. They tell you stories of why they can't pay their loans, and they are usually good stories. The last thing these people need is leniency, you have to be tough with them, you have to pressure them until they pay […] The policies are very clear on this. (The clients) signed a contract and they must abide by it. Otherwise they all learn that it is OK not to pay and other clients can see this and do the same. (LL officer)*

In that sense, SL officers who may seem lenient when a payment is missed may simply have more information, gathered through personal relationships with clients, to interpret an otherwise noisy signal. Given that a set of boundaries –social, economic, cultural—exist between clients and the MFI, policies may miss important elements that can be relevant, especially during atypical situations like an exogenous shock. SL officers construct bridges across those boundaries:

> *Officers are information brokers. They have information on each of their clients and sometimes of the people the clients know. They can use that information to determine the moral and economic solvency of new prospects, to detect when a client is in trouble, and to be more effective when they need to collect (…) they have seen what works and what doesn't (…) They know who does what and who know who. When officers use that information to benefit a client, they can truly make a difference. (Regional Manager, Urban)*

Table A1, below, compares observable characteristics across loan officer styles to ensure that the categorization is not capturing something other than their relational style. For example, a particular concern may be that Mixed loan officers are less experienced with policies, are less well known by their managers, or simply did not stay in the firm long enough to develop a style. The data show, however, that observable characteristics are virtually identical across styles, which minimizes concerns that the typology is driven by an omitted (and problematic) variable.

TABLE A1

CROSS-TABULATION AND TEST OF DIFFERENCES IN LOAN OFFICER CHARACTERISTICS BY RELATIONAL ENFORCEMENT STYLE

				T Test of difference in means		
		(SD in parentheses)		*(SE of difference in brackets)*		
Loan Officer Type	**Spirit**	**Letter**	**Mixed**	**S - L**	**S - M**	**L - M**
Tenure (Days)	990.70	996.00	948.90	0.06	0.52	0.56
	(742.5)	(760.9)	(628.1)	(85.47)	(80.94)	(83.83)
Total branch rotations	5.30	5.19	5.88	1.01	0.39	1.4
	(7.917)	(6.958)	(8.705)	(0.959)	(0.909)	(0.941)
Left firm (%)	0.54	0.58	0.57	1.3	0.59	0.77
	(0.492)	(0.470)	(0.484)	(0.058)	(0.055)	(0.056)
Time in first branch (months)	10.92	9.11	8.90	1.18	2.08#	0.8
	(9.599)	(8.759)	(7.290)	(1.032)	(0.978)	(1.013)
Technical degree	0.11	0.09	0.12	0.66	0.27	0.93
	(0.313)	(0.280)	(0.325)	(0.037)	(0.036)	(0.036)
College degree	0.79	0.78	0.75	0.28	0.81	0.5
	(0.409)	(0.419)	(0.434)	(0.050)	(0.048)	(0.050)
Gender	0.41	0.46	0.36	0.95	0.94	1.87
	(0.493)	(0.501)	(0.480)	(0.057)	(0.055)	(0.058)
Age	28.15	26.67	26.75	2.57**	2.31#	0.38
	(4.939)	(4.369)	(4.288)	(0.579)	(0.546)	(0.574)
Married	0.36	0.30	0.26	1.41	1.88	0.36
	(0.483)	(0.451)	(0.441)	(0.057)	(0.053)	(0.054)
Average loan	8.79	8.32	8.79	1.46	0	1.49
	(3.509)	(2.055)	(2.110)	(0.320)	(0.303)	(0.314)
Average interest rate	81.56	85.02	81.39	1.13	0.45	1.59
	(3.508)	(3.378)	(3.146)	(0.403)	(0.382)	(0.395)

Source: Unique dataset of ≈450,000 microfinance loans made in Mexico, 2004 -2008

Note: *P <.1, **P <.05, # insignificant at P <.05 with Bonferroni adjustment (two-tailed tests). For proportions, a z-test of the difference was performed.

TABLE A2: LOGISTIC REGRESSION PREDICTING TWO MISSED PAYMENTS IN A LOAN CYCLE

	21	22	23	24	25	26	27	28	29
VARIABLE	b/(SE)	b/(SE)	b/(SE)	b/(SE)	b/(SE)	b/(SE)	b/(SE)	b/(SE)	b/(SE)
Spirit$_t$ (H1)	-0.444								
	(0.011)***								
Letter$_t$ (H1)	-0.361								
	(0.013)***								
Δofficer change$_{t,t+1}$		0.581	0.545	0.337	0.477	0.392			
		(0.024)***	(0.019)***	(0.021)***	(0.022)***	(0.029)***			
Along Consistent$_{t,t+1}$ (H2)		-0.198					-1.058		
		(0.038)***					(0.046)***		
Individually consistent$_t$→ Individually consistent$_{t,t+1}$ (H2)		-0.166					-1.045		
		(0.039)***					(0.049)***		
Individually inconsistent$_t$ →Individually inconsistent$_{t+1}$ (H2)		-0.058		0.186	0.033	0.13	-0.125		0.983
		(0.022)***		(0.024)***	(0.023)	(0.030)***	(0.025)***		(0.034)***
Individually inconsistent$_t$→ Individually consistent $_{t+1}$ (H3)		-0.282					-1.142		
		(0.028)***					(0.038)***		
Spirit$_t$→spirit$_{t+1}$ (H2)			-0.225		-0.154	-0.072		-1.027	
			(0.044)***		(0.045)***	(0.04)		(0.058)***	
Spirit$_t$→letter$_{t+1}$ (H2)			-0.116					-0.972	
			(0.045)**					(0.063)***	
Letter$_t$→letter$_{t+1}$ (H2)			-0.067					-0.957	
			(0.054)					(0.068)***	
Letter$_t$→spirit$_{t+1}$ (H2)			-0.145			0.009		-0.982	
			(0.055)***			(0.059)		(0.070)***	
Mixed$_t$→spirit$_{t+1}$ (H3)			-0.277		-0.206	-0.125		-1.092	
			(0.030)***		(0.032)***	(0.037)***		(0.046)***	

Mixed$_t$→letter$_{t+1}$ (H3)			-0.201					-1.047	
			(0.035)***					(0.051)***	
Spirit$_t$→mixed$_{t+1}$ (H3)				0.222	0.071	0.168			1.062
				(0.029)***	(0.029)**	(0.035)***			(0.039)***
Letter$_t$ →mixed$_{t+1}$ (H3)				0.268		0.215			1.169
				(0.033)***		(0.038)***			(0.043)***
LO fixed-effects	NO	YES	YES	YES	YES	YES	YES	YES	YES
Branch fixed-effects	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year fixed-effects	YES	YES	YES	YES	YES	YES	YES	YES	YES
SAMPLE/ RESTRICTIONS							Condition on LO change	Condition on LO change	Condition on LO change
Model fit/diagnostics									
N	438,157	438,346	438,346	438,346	438,346	438,346	112,188	112,188	112,188
χ^2	33,719***	34,120***	34,112***	34,109***	34,081***	34,117***	9,892***	9,874***	9,890***

Source: Proprietary, loan-level database of microfinance loans from one urban-focused MFI in Mexico, 2004-2008
Note: ****P*<.001; ***P*<.01; **P*<.05 (two-tailed tests)
The dependent variable is dichotomous and takes the value of one if, within a loan cycle, a client has missed two payments. Where indicated, models also include loan officer fixed effects. In addition, all models include the controls outlined in the previous tables, which are omitted for presentation purposes. Controls remain stable across models.
The omitted category for model 21 is a mixed style. For models 22 and 27 the omitted category is individually consistent to individually inconsistent; in models 23 and 28 it is LL or SL to mixed; for model 24 or 29 it reflects any style-specific movement from mixed to something else, or between LL and SL; and for models 25 it is any movement to or from LL and for 26 it is any movement to LL.

TABLE A3: LOGISTIC REGRESSION PREDICTING THREE MISSED PAYMENTS IN A LOAN CYCLE

	30	31	32	33	34	35	36	37
VARIABLE	b/(SE)	b/(SE)	b/(SE)	b/(SE)	b/(SE)	b/(SE)	b/(SE)	b/(SE)
Spirit_t (H1)	-0.564							
	(0.013)***							
Letter_t (H1)	-0.481							
	(0.015)***							
$\Delta\text{officer change}_{t,t+1}$		0.723	0.691	0.441	0.606			
		(0.028)***	(0.023)***	(0.026)***	(0.026)***			
$\text{Along Consistent}_{t,t+1}$ (H2)		-0.287				-1.214		
		(0.045)***				(0.053)***		
Individually Consistent_t→ Individually Consistent_{t+1} (H2)		-0.167				-1.13		
		(0.045)***				(0.056)***		
Individually inconsistent_t →Individually $\text{inconsistent}_{t+1}$ (H2)		-0.052		0.231	0.05	-0.128		1.109
		(0.025)**		(0.028)***	(0.027)*	(0.028)***		(0.039)***
Individually inconsistent_t →Individually consistent_{t+1} (H3)		-0.319				-1.274		
		(0.033)***				(0.043)***		
Spirit_t→spirit_{t+1} (H2)			-0.321		-0.235		-1.213	
			(0.053)***		(0.055)***		(0.068)***	
Spirit_t→letter_{t+1} (H2)			-0.14				-1.049	
			(0.053)***				(0.072)***	
Letter_t→letter_{t+1} (H2)			-0.156				-1.07	
			(0.065)**				(0.078)***	
Letter_t→spirit_{t+1} (H2)			-0.116				-1.066	
			(0.065)*				(0.081)***	
Mixed_t→spirit_{t+1}			-0.33		-0.246		-1.249	

(H3)			(0.036)***		(0.038)***		(0.053)***	
Mixed$_t \rightarrow$letter$_{t+1}$			-0.223				-1.142	
(H3)			(0.042)***				(0.058)***	
Spirit$_t \rightarrow$mixed$_{t+1}$				0.275	0.095			1.201
(H3)				(0.034)***	(0.033)***			(0.043)***
Letter$_t \rightarrow$mixed$_{t+1}$				0.29				1.284
(H3)				(0.038)***				(0.048)***
Loan officer fixed-effects	NO	YES	YES	YES	YES	YES	YES	YES
Branch fixed-effects	YES	YES	YES	YES	YES	YES	YES	YES
Year fixed-effects	YES	YES	YES	YES	YES	YES	YES	YES
SAMPLE/ RESTRICTIONS						Condition on LO change	Condition on LO change	Condition on LO change
Model fit/diagnostics								
N	437,913	438,346	438,346	438,346	438,346	112,188	112,188	112,188
χ^2	28,860***	27,983***	27,976***	27,975***	27,953***	8,510***	8,496***	8,506***

Source: Proprietary, loan-level database of microfinance loans from one urban-focused MFI in Mexico, 2004-2008
Note: ****P*<.001; ***P*<.01; **P*<.05 (two-tailed tests)
The dependent variable is dichotomous and takes the value of one if, within a loan cycle, a client has missed three payments. Where indicated, models also include loan officer fixed effects. In addition, all models include the controls outlined in the previous tables, which are omitted for presentation purposes. Controls remain stable across models.
The omitted category for model 30 is a mixed style. For model 31 and 35 the omitted category is individually consistent to individually inconsistent; in models 32 and 36 it is LL or SL to mixed; for model 33 or 37 it reflects any style-specific movement from mixed to something else, or between LL and SL; and the omitted category in model 34 is any movement to LL.