Repayment Concentration and Consumer Motivation to Get Out of Debt

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TECHNICAL WEB APPENDIX:

ROBUSTNESS CHECKS FOR THE FIELD DATA ANALYSES

The results provided in the manuscript provided the first evidence that the use of a more concentrated repayment strategy in one month led to repayment of greater magnitude in the next month. The robustness of our results depends on our inclusion of key variables, and we included the measure of concentration of the debt across accounts ($acctconc_{it}$), debt in the previous month ($debt_{i(t-1)}$), the total amount spent ($tspend_{i(t-1)}$), the number of cards held by the indebted consumer ($nbcards_{i(t-1)}$) and whether at least one account's balance was brought down to \$0 (i.e., closed, $acctrepaid_{i(t-1)}$). We also included month and year indicators to control for seasonality and period shocks that are consumer independent. We estimated the coefficients fixed-effect specification which allowed us to control for different initial conditions (e.g., debt levels) and for individual characteristics that are stable across time periods (e.g., personality traits). These results are duplicated in table A1's model 1.

In the present section, we provide analyses for the robustness of the observed effect of a concentrated repayment strategy on subsequent repayments with respect to omitted variables bias, alternative model specifications, and concerns of reverse causation and endogeneity of the focal predictor. We do so by presenting the results from three alternative models (Table A1's Models 2-4).

Alternative Specifications

In Model 1, we included several characteristics of the debt structure (size of the debt, total spent, and concentration of the debt, debt repaid in the previous month) as control variables. It is possible that the variance explained by our key measure ($conc_{i(t-1)}$) could be reduced if we include further lags for these debt characteristics that could explain both one's tendency to engage in a concentrated repayment strategy and how much one would repay in the following month. It is thus possible such omitted variables have resulted in (positively) biased estimates of the effect of the repayment strategy on repayments. As such in model 2, we included additional lags.

Our results are consistent. The repayments in month t seemed to still be influenced by the prior month ($\beta = .16, p < .01$) by not the one prior to that ($\beta = .09, p = .29$). We continue to fail to find evidence that the number of cards held ($\beta = -53.05, p = .60$), the closing of an account ($\beta = -46.25, p = .68$) and the concentration of the debt remaining ($\beta = -524.06, p = .11$) influence the magnitude of the repayments. We also fail to find an effect of the concentration of debt in the previous month ($\beta = -418.28, p = .19$). We do find that the magnitude of spending in both the prior ($\beta = -.17, p = .02$) and second-prior ($\beta = -.19, p = .04$), and that the total about of debt owed also had an effect for more than one period ($\beta = -.06, p < .01$). Yet, crucially, controlling for all these additional factors the effect of a concentrated repayment strategy on subsequent repayments is significant ($\beta = 621.89, p < .01$). Another possibility is that our results depend on whether the large repayments made through a concentrated strategy are applied to debt accounts that are naturally more concentrated in nature. This was tested, in model 3, via an interaction between $conc_{i(t-1)}$ and $account_{it}$ for which we failed to find significant evidence ($\beta = -315.33, p = .58$). Further, despite the addition of this interaction, all other conclusions remain identical. Taken together, the results from both of these additional models provide evidence that our finding regarding the effect of a concentrated strategy on subsequent debt repayments is robust to the inclusion of several additional controls and variables.

Endogeneity Concerns

The models above incorporated fixed effects that account for individual time-invariant characteristics that we cannot observe (e.g., personality trait, age, gender) that could simultaneously influence one's tendency to generally engage in a concentrated repayment strategy and one's tendency to generally make greater repayments in the following month. That is, our results are robust to such individual-level characteristics and to unobservable monthly and yearly shocks. Yet, it remains possible that unobserved variables that are time-variant explain both one's tendency to use a concentrated repayment strategy (in a given month) also influence their tendency to repay more in the following month. Further reverse causality (i.e., the tendency to make large repayments influences the strategy used in the following model) remains possible as well, creating concerns of endogeneity.

Whereas one possibility would be to use instrumental variables such that the instruments are correlated with $conc_{it}$ but not ϵ_{it}, no such variables (instruments) naturally exist in our data. Instead, we used Arellano and Bond's (1991) differentiated GMM procedure to obtain consistent parameter estimates and asymptotic covariance (see also Dutt and Padmanabhan 2011; Ho-Dac, Carson and Moore 2013; Tuli, Bharadwaj and Kohli 2010). The use of the differentiated GMM procedure, which is common practice in the analysis of dynamic panel data in the marketing literature (see also Derdenger and Kumar 2013; Narasimhan, Rajiv and Dutta 2006; Shah, Kumar, and Kim 2014; Xiong and Bharadwaj 2013), protects against key threats to causal inference (unmeasured confounding variables and reverse causation).

Regarding the presence of omitted time-invariant individual variables, the difference GMM procedure provides estimates of $\Delta repay_{it} = repay_{it} - repay_{i(t-1)}$. Note that as both $repay_{it}$ and $repay_{it-1}$ include the same unobserved ν_i, differencing results in $\nu_i - \nu_i$ and thus removes any effect from unobserved individual difference or personality trait that may influence our estimates for our variables of interest. Whereas taking the first difference removes the intercept and any omitted time invariant variables, there is still possible correlation between the differenced lagged dependent variables and the difference error terms. Arellano and Bond (1991) suggested that given that the individual fixed effects have been removed by first-differencing, we can construct instruments from the past information of $repay_{it}$ as instruments. If $\Delta repay_{it} = \beta_1\left(repay_{i(t} - repay_{i(t-1)}\right) + \left(\epsilon_{it} - \epsilon_{i(t-1)}\right)$, then $repay_{i(t-2)}$ is not correlated with the error $(\epsilon_{it} - \epsilon_{i(t-1)})$ but rather with $(\epsilon_{i(t-1)} - \epsilon_{i(t-2)})$, and $repay_{i(t-2)}$ can thus be used as a valid instrument and obtain one-step consistent estimators. We used second period lags as instruments in both the difference equations and the equations in level, and we did so while considering total debt and total spending as also potentially endogeneous. We note that we use robust estimators of the covariance matrix to obtain standard errors for the coefficients. Our results, including the relevant statistics, are presented in table A1.

The results from the model are also consistent with those obtained by the fixed-effects model presented. The effect of a concentrated strategy on subsequent repayment is significant $(\beta = 2411.67, p = .02)$. We still find that the effect is robust on the inclusion of other controls. We still find no evidence for an effect of concentration of the debt accounts ($\beta = -590.79, p =$

.77), the number of cards ($\beta = 333.15, p = .21$) and having just fully repaid an account ($\beta = -1097.38, p = .11$). For the other control variables, the test-statistics provide identical conclusions.

This approach to modeling dynamic panel data relies on three key assumptions. First, there should be no second-order serial correlation in the residuals. This can be tested with the AR(II) statistic developed by Arellano and Bond (1991) which in our case provided no evidence for the presence of second-order serial correlation ($Z = -.05, p = .61$). Second, the assumption that the model and overidentifying conditions are correctly specified can be investigated using the Hansen J statistic, which has a null hypothesis that the instruments are valid. Our results suggest that the model is correctly specified ($\chi^2(213) = 213.4, p = .48$). Third, the instruments used appear to indeed be exogenous (difference-in-hansen statistic, $\chi^2(120) = 128.2, p = .29$).

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Table A1

Field Data: Alternative Model Specifications

	Fixed Effect Regressions									Arellano Bond		
	Model 1			Model 2			Model 3			Model 4		
	β	t	p	β	t	p	β	t	p	β	stat	p
intercept	-485.04	-0.81	0.42	-162.63	-0.28	0.78	-276.78	1.28	0.20	-1440.93	-1.13	0.26
$repay_{i(t-1)}$	0.23	3.78	0.00	0.16	2.64	0.00	0.16	2.64	0.08	0.76	6.47	0.00
$repay_{i(t-2)}$				0.09	1.06	0.29	0.09	1.05	0.29	0.42	2.47	0.01
$conc_{i(t-1)}$	558.65	3.75	0.00	621.89	3.94	0.00	725.01	2.70	0.00	2411.67	2.33	0.02
$acctconc_{it}$	-172.62	-0.57	0.57	-524.06	-1.61	0.11	-516.14	-1.30	0.20	-590.79	-0.29	0.77
$conc_{i(t-1)} : acctconc_{it}$							-315.33	-0.55	0.58			
Controls												
$debt_{it}$	0.24	4.99	0.00	0.22	7.33	0.00	0.23	7.36	0.00	0.18	2.03	0.04
$debt_{i(t-1)}$				-0.06	-2.89	0.00	-0.06	-2.85	0.00	-0.15	-1.76	0.08
$tspend_{i(t-1)}$	-0.29	-4.64	0.00	-0.17	-2.41	0.02	-0.17	-2.42	0.02	-0.78	-4.61	0.00
$tspend_{i(t-2)}$				-0.19	-2.09	0.04	-0.18	-2.03	0.04	-0.51	-2.79	0.01
$nbcards_{i(t-1)}$	-238.79	-1.53	0.10	-53.05	-0.53	0.60	-53.92	-0.54	0.59	333.15	1.26	0.21
$acctrepaid_{i(t-1)}$	36.61	0.37	0.71	-46.25	-0.42	0.68	-41.70	-0.38	0.71	-1097.38	-1.59	0.11
$acctconc_{i(t-1)}$				-418.28	-1.32	0.19						
Observations (YM)	8699.00			7440			7440			7440		
Consumers	1094			989			989			989		
R^2 (within)	0.1418			0.1174			0.1171					
Number of Instruments										237		
AR(2) in first differences											-0.051	0.611
Hansen test											213.4	0.479
Difference in Hansen											128.17	0.288